DOCTOR OF PHILOSOPHY

The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets

Bello, Jaliyyah

Award date:
2014

Awarding institution:
Coventry University

The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets

By

Jaliyyah Ahmadu-Bello

PhD

September 2014

Coventry University

The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets

By

Jaliyyah Ahmadu-Bello

A thesis submitted in partial fulfilment of the University's requirements for the Degree of Doctor of Philosophy

September 2014

Declaration

I hereby declare that this research has been conducted solely by me under the guidance of my Director of studies, Dr Timothy Rodgers. I had neither copied someone's work nor has someone done it for me. Relevant works by other authors have been duly acknowledged in this research.

Dedication

To my parents, siblings and the rest of my family.

To my family friends, friends and colleagues at Coventry University.

To the Doctors, Nurses and other health care Staff of University Hospital Coventry and Warwickshire, Coventry.

I could not have done it without you all!

Abstract

This thesis tests financial contagion from the US to ten African markets during the 2007-09 financial crisis. For comparative purposes, testing procedures are also extended to cover a number of developed-economy markets.

There is considerable debate within the literature as to how to measure contagion. A central focus of my research is therefore to compare alternative econometric methodologies. VAR based constant-correlation based techniques are examined alongside dynamic conditional correlation (DCC) based techniques. I find that the DCC approach is superior in respect to my dataset.

The 2007-09 crisis was unique from a contagion perspective in that its impact was truly global. This provided a unique opportunity to examine the subject across different continents and market types. African markets were found to have lower levels of integration (correlation) with the US than developed-economy markets and this resulted in considerable differences in the way that the contagion event spread across these two groups.

As well as being truly global, the 2007-09 crisis was a contagion event that lasted more than a year. I use the volatility index (VIX) to identify both a long crisis period and a series of sub-events. The former ran from 15 September 2008 to 15 October 2009. The four sub-events were 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

Correlations (and contagion) changed significantly as sub-events unfolded. At the onset of the crisis, correlations with *all* African markets increased relatively quickly. I suggest that this can possibly be considered as being consistent with fast *herding*

behaviour. The impact on developed markets was very different in that contagion spread slowly. I suggest that this can possibly be considered as being consistent with *slow herding*.

I argue that differences in contagion found between African and developed markets reflect differences in *social network effects* in investor communities. I apply behavioural finance theory to more fully explore this issue and identify the channels through which contagion events developed.

Table of Contents

List of Tables

List of Figures

Acronyms and Abbreviations

4E Journal	Education Examination Experience Ethics Journal
ABC	Asset Banking Currency
ADRs	American Depository Receipts
AfDB	African Development Bank
AIC	Akaike information criterion
AR	Auto Regression
ARCH	Autoregressive Conditional Heteroscedasticity
ASEA	African Securities Exchanges Association
BEKK	Baba Engle Kraft and Kroner
BIC	Bayesian information criterion
BNP	Banquet Nationale De Paris
BRVM	Bourse Régionale des Valeurs Mobilières
BSE	Botswana Stock Exchange
BSE	Bombay Stock Exchange
BWA	Botswana
CAC 40	Cotation Assistée en Continu 40
CAN	Canada
CAPM	Capital Asset Pricing Model

CASE	Cairo & Alexandria Stock Exchange
CEA	Chinese Economic Area
CFA	Chartered Financial Analyst
CHN	China
CIV	Cote d'Ivoire
CSE	Casablanca Stock Exchange
DAX	Deutscher Aktien Index
DCC	Dynamic Conditional Correlation
DJIA	Dow Jones Industrial Average
DJIJ	Dow Jones Islamic Index of Japan
DJIMKW	Dow Jones Islamic Index of Kuwait
DJIMTR	Dow Jones Islamic Index of Turkey
DJIMY	Dow Jones Islamic Index of Malaysia
DJIUK	Dow Jones Islamic Index of UK
EconLit	Economics Literature
EGX	The Egyptian Exchange
EGY	Egypt
EIB	European Investment Bank
FDI	Foreign Direct Investment

FR	Forbes and Rigobon
FRA	France
FT	Financial Times
FTSE	Financial Times Stock Exchange
GARCH	The Generalised Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GER	Germany
GJRGARCH	Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroscedasticity
GMT	Greenwich Mean Time
HBOS	Halifax and Bank of Scotland
HQC	Hannan Quinn Criterion
ICAPM	Intertemporal Capital Asset Pricing Model
ICSS	Iterated Cumulative Sum of Squares
IFCI	International Finance Corporation Investibles
IGPA	Indice General de Precios de Acciones
IKB	Industrie Kredit Bank
IMF	International Monetary Fund
IMUS	Dow Jones Islamic Index of America

IND	India
ITA	Italy
JAKIS	Jakarta Islamic Stock Index
JPN	Japan
JSE	Johannesburg Stock Exchange
LuSE	Lusaka Stock Exchange
MAR	Morocco
MENA	The Middle East and North Africa
MGARCH	Multivariate Generalised AutoRegressive Conditional Heteroscedasticity
MLA	Myopic Loss Aversion
MSCI	Morgan Stanley Capital International
MUS	Mauritius
NAM	Namibia
NASDAQ	National Association of Securities Dealers Automated Quotations
NGA	Nigeria
NGARCH	Nonlinear Generalised AutoRegressive Conditional Heteroscedasticity
NIKKEI	Nihon Keizai Shimbun
NSE	The Nigerian Stock Exchange
NSX	Namibian Stock Exchange

OLS	Ordinary Least Squares
RBS	The Royal Bank of Scotland
RIC	Reuters Instrument Code
S&P	Standard and Poor’s
SA	South Africa
SEMDEX	Stock Exchange of Mauritius Index
SPN	Spain
SSEASI	Shanghai Stock Exchange A Share Index
TARP	Troubled Asset Relief Program
TGARCH	Threshold Generalised AutoRegressive Conditional Heteroscedasticity
TSB	Trustees Savings Bank
TSE	Tunis Stock Exchange
TSX	Toronto Stock Exchange
TUN	Tunisia
UK	United Kingdom
UNDP	United Nations Development Programme
US	United States
USD	United States Dollars
UTC	Coordinated Universal Time

VAR	Vector Autoregressive
VIX	Volatility Index
ZMB	Zambia

1 INTRODUCTION

1.1 CONTAGION BACKGROUND

The term “*contagion*” became widely used in the financial lexicon following the seminal works of King and Wadhwani (1990) and Forbes and Rigobon (2002) on the 1987 and 1990s financial crises. The term is usually defined in terms of “a significant increase in cross-market linkages resulting from a shock hitting one country or group of countries” (Forbes and Rigobon 2002:2223).

Contagion has become increasingly significant within the academic literature in recent years. Searching for the word “contagion” in the *EconLit* database over the period 1969-2000, Edwards (2000) found it returned 147 entries. In comparison, “devaluation” (a word strongly associated with the 1990s crises) returned 1,031. Following Edwards (2000), I ran a similar search from 1990 to 2011. This yielded 1,446 entries for contagion and 1,560 for devaluation. This is indicative of the pace at which research on contagion has increased following the 1990s crash and the recent 2007-2009 global financial crisis.

Within the contagion literature the strongest focus is on the 1997 Asian financial crisis, the 1998 Russian financial crisis and the Mexican economic crisis in 1994. Other studies have examined the Brazilian crisis of 1999 and the European exchange rate mechanism collapse of 1992. More recently we have started to see studies relating to the 2007-09 crisis and I hope to be able to make a contribution in this area.

Financial contagion has been viewed in literature as mainly a concern for emerging markets, markets of similar structures or belonging to the same region. For instance, the great depression of 1929, which affected primarily the United States and Europe; the

United States market crash of 1987, which led to the fall of major stock markets in developed markets such as the London Stock Exchange and Tokyo Stock Exchange; and the 1997 devaluation of the Thai baht, which created crises in Asian countries.

Although, the origin of the 2007-09 crisis was located as the US, the effects were not limited to markets of similar structures or in the same geographical area. As a result it became known as the "*global financial crisis*"; even the media could not find a more suitable name. The unique and never-before-seen nature of this crisis has presented academics with the opportunity to develop further their understanding of contagion and I hope to make a contribution to this in this thesis.

The 2007-09 crisis saw many developed-country markets suffer greatly as a result of exposure to US sub-prime mortgages. Huge investment banks (Bear Sterns, Lehman Brothers, BNP Paribas and IKB Industriebank) across the US and European countries had to be bailed out or went bankrupt. In African markets the effects of the crisis did not become apparent until late 2008. When it did manifest itself it was most apparent in the larger and most liquid markets, namely, Egypt and Nigeria. Losses in these markets during the financial turmoil surpassed losses in any developed market in percentage terms (AfDB, 2009).

How severe was this crisis and what caused it? Malik et al. (2009:86) argued it was "the most severe since the stock market crash of 1929". Bartlett (2008:2) argues there were a series of reasons for it. He identified that: "mark-to-market losses on mortgage-backed securities, collateralised debt obligations and related assets through March 2008 approximate $945 billion. In absolute terms this represents the largest financial loss in history, exceeding asset losses resulting from Japan's banking crisis in the 1990s ($780 billion) and far surpassing losses emanating from the Asian crisis of 1997-98 ($420 billion) and the US savings and loan crisis of 1986-95 ($380 billion)".

1.2 THE THESIS: GENERAL PHILOSOPHY

Within the existing literature, a number of studies have focused on identifying the causes and channels of transmission of financial contagion. As will be examined in Chapter 2, these factors include asset market effects, banking and currency channels, fundamental effects such as common shock and trade effects, investor behaviour-related effects, and issues relating to liquidity problems and information asymmetries. I would add another issue to this list; I believe that the study on financial crisis needs to consider the impact of differences in the extent of *financial market integration* between the source country (US) and contaminated country.

As the contagion literature has developed, so has the number of competing econometric methodologies that can be applied. This thesis identified that this makes it difficult to select a preferred one. The most widely used tests for contagion effect are based around *constant correlation* coefficient analysis and *dynamic conditional correlation* coefficient analysis. Other approaches are based around co-integration techniques and the direct mechanism approach (Chapter 3, Section 3.4.1). The thesis applies first, constant correlation coefficient analysis (Chapter 4), based on the work of Forbes and Rigobon (2002), and, second, dynamic conditional correlation analysis (Engle 2002) in Chapter 5. These approaches are used to examine the correlation of daily market returns between the US market and selected African markets, and the US and selected developed markets. High-growth non-African emerging markets are included for comparative purposes.

As well as focusing on the econometric issues relating to the measurement of contagion, this thesis also has a second objective of identifying the channels that contagion follows. A promising avenue to follow in this respect is presented by behavioural finance theory, given that uncertainty is the key driver of behaviour during crisis situations. The thesis discusses whether behavioural drivers such as herding might have a role to play in contagion and whether differences can be identified in respect to contagion events in Africa and contagion events in developed markets.

The 2007-09 crisis was different in that it was not a single short sharp shock, but was an event that unfolded in the US over a period of more than a year. The event can be characterised as being a series of crisis waves (see Figure 3.5, Chapter 3). The question arises from a behavioural perspective of how will the markets respond? Will they treat each sub-event as separate and unrelated and *anchor* their decisions on the US market in each instance? Will they become used to crisis in the US and stop responding to events in the US altogether? Or will each sub-crisis in the US have a diminishing impact on these African markets? These are the types of questions I consider in this thesis.

1.2.1 The Thesis: Scope

The contagion literature is vast, with a large number of alternative competing objectives and methodologies. It is therefore important to be clear in respect to the scope of my work. The scope of the research is outlined as follows:

1. The research shall focus on the relationship between the US (using the S&P500 index) and ten emerging/frontier African stock markets. Academic research generally categorises the impact of financial crisis in terms of (i) contagion (ii) interdependence (iii) spill-over effect (see Figure 3.4 for details). The scope of

the thesis is limited to examining contagion effects. The thesis did not test for secondary spill-over effect from the largest market in Africa, the Johannesburg stock exchange, to other markets within the African continent. This is because the thesis focuses on testing the direct vulnerability of African markets to the crisis of a developed market (US).

It would not have been overly surprising if contagion did exist between South Africa and other African countries, especially, in the presence of regional integration which exists in the different sub regions of Africa. All the African markets in this thesis are members of African Stock Exchanges Association (ASEA) whose plan is to eventually integrate African markets. ASEA also stand to provide first-hand information to investors on African markets. An examination of these effects could possibly be made the subject of post-doctoral research.

2. For comparative purposes the relationship between the US and a number of developed and high-growth emerging markets are also examined.
3. The methodological scope of the thesis is limited to the constant correlation coefficient analysis and the dynamic conditional correlation (DCC) analysis. It is identified in Chapter 6 (Section 6.3) that DCC can be applied from an asymmetric correlation approach (Asai 2013). This thesis considers this approach beyond its scope, given that it had not come into the mainstream literature until after the thesis was started.
4. The thesis is also limiting the scope of the behavioural analysis to the interpretation of the econometric results. The undertaking of surveys as seen in other parts of behavioural literature (Aduda, Oduor and Onwonga 2012, Lowies,

Hall and Cloete 2013, Shiller, Konya and Tsutsui 1988) could be another PhD in itself.

It is observed from the review of literature that previous studies on financial contagion relating to the 1990s crises largely ignored African markets (except South Africa). This was possibly a reflection of the low level of correlations between African market and developed markets at the time. As such, previous studies on financial contagion are unlikely to have much relevance to African Investors. It is however, noted that African stock market have developed dramatically over the last 10-15 years. This resulted in the linkages between US and African markets becoming stronger. The changes that have occurred means studying financial contagion in Africa is now of utmost relevance.

It is also identified in Section 2.8 page 96, that a further motivation of the study is to examine possible behavioural explanations for differences in contagion from US to Africa and from US to other developed markets. The discussions of my result in this context are provided in Chapter 6.

1.2.2 Research questions

The justifications for my research questions are given in Chapter 2, where they are presented in the context of the existing academic literature. These research questions are summarised as follows:

1. Methodology: to identify which of the *constant correlation* and the *dynamic conditional correlations* methodologies are most appropriate for the examination of contagion effects in Africa and selected other international markets.
2. The application of contagion testing to a cross-section of both emerging and frontier African markets.

3. Identifying the channels through which contagion events develop within the context of appropriate theory (behavioural and/or non-behavioural models).
4. Identifying differences in the ways that contagion events unfold in developed markets and emerging/frontier African markets (in the context of appropriate behavioural and/or non-behavioural models).

1.3 THESIS NOVEL CONTRIBUTIONS

- ***The thesis adds to our knowledge of contagion from the US to a broad cross-section of African markets. The thesis has also undertaken a comparative study of the contagion effects found in African markets and developed markets. It has found differences in these groups.***

The author of the thesis asserts that very few studies exist on financial contagion regarding African markets. Most studies in this area are focused on the emerging markets of Asia, Latin America and Europe. Collins and Biekpe (2003), Morales and Andreosso-O'Callaghan (2010) and Asongu (2011a and 2011b) have incorporated African markets in their study but this was done on a limited basis. This thesis will therefore contribute to literature in terms of a more in-depth application of contagion modelling to African markets. Furthermore, the thesis compares the level of contagion found in African markets and those found in developed markets. Clear differences are evident in both correlation levels and evidences of contagion found in the two groups of markets.

- ***The thesis contributes to the analysis of the financial contagion from the perspective of behavioural finance theory in both African and developed market contexts. The principle finding being the differences in suggested behavioural biases affecting the two groups.***

This thesis develops a model of the channels that financial crisis follows (Figure 3.12, Chapter 3). The thesis also contributes to contagion literature in terms of identifying behavioural-based channels and identifying differences in respect to these channels in relation to African and developed markets (Chapter 6).

- ***The thesis has identified that the use of DCC to measure contagion is the preferred statistical methodology, given the problems found in applying alternative methodologies.***

The different methodologies are applied in Chapters 4 and 5 of the thesis, and which is the most appropriate methodology to use is discussed in Chapter 6. This is undertaken in the context of the dataset that the application is made to.

1.4 THESIS STRUCTURE

The thesis is essentially divided into six main parts, as follows:

1 **Introduction (Chapter 1):** This provides a background on contagion and introduction to the thesis topic. The scope of the thesis and the research questions are identified in this chapter.

2 **Literature (Chapter 2):** Definitions, theories and empirical evidence of contagion is examined in this chapter. The chapter also discusses financial integration and behavioural finance. The chapter provides the foundation for Chapters 3, 4 and 5 and the theoretical discussion in Chapter 6.

- *Major objectives of this chapter are to understand financial contagion, its guiding theories and to identify gaps from existing studies on financial contagion.*

3 **Data, methodological notes and hypotheses development (Chapter 3):** The type of data used and sources of data are the starting point of this chapter. The statistical hypotheses tested in the thesis are developed here along with a proposed theoretical model of the channels of contagion.

- *Major objective of this chapter is to create a process flow from the type of data used, methodology employed, hypotheses developed and expected results.*

4 **Empirical tests (Chapters 4 and 5):** Chapter 4 deals with the first testing framework adopted for the thesis, which is the correlation coefficient analysis adjusted as per Forbes and Rigobon (2002). This chapter also embodies a novel contribution to the thesis in terms of the correlation coefficient analysis. Chapter 5 is the application of the second testing framework, which is the dynamic conditional correlation analysis based on GARCH (1, 1). This chapter also carries out a test of robustness using dummy variables to strengthen the findings of the DCC approach.

- *The objective of these chapters is to test if contagion has occurred during the 2007-09 financial crisis*.

5 **Comparative discussion of results and application of proposed model (Chapter 6):** The findings of Chapters 4 and 5 are discussed in this chapter in a pair-wise approach. First the chapter compares the methodologies of Chapters 4 and 5. It then examines the evidence for contagion found in the African and developed markets. The theoretical model proposed in Chapter 3 is applied to the interpretation of the results.

- *The objective is to provide an understanding of the results obtained in Chapters 4 and 5.*

6 **Conclusions and future research areas (Chapter 7):** The final part of the thesis summarises the study. This chapter provides a summary of major findings, a summary of novel contributions and identifies potential future research areas.

- *The objective of this chapter is to summarise the whole thesis and identify areas where my work could be developed further in the future.*

2 THEORETICAL REVIEW OF LITERATURE[1]

2.1 INTRODUCTION

The period under study (2007 to 2009) witnessed the worst financial crisis since the Great depression of 1929. This event sparked greater interest on the impact of the financial crisis of one country on another, otherwise referred to as ***financial contagion***. The definition of financial contagion depends largely on what information researchers are looking for from their data. As such, definitions vary among researchers. In view of this, several definitions of the term and what contagion constitutes are discussed in Section 2.2.

Contagion literature is vast and difficult to systemise. To develop a framework for examining this literature, Section 2.3 explores the different theories of contagion in terms of the *causes of contagion* (fundamental and investor behaviour) *and channels of contagion* (asset market, banking and currency channels). This section also provides an overview of the different testing methodologies (Section 2.3.3). Fuller details of the different methodologies are discussed in Chapters 3, 4 and 5.

Although many models of contagion in the literature attempt to explain the process using behavioural-finance-related terms such as “herding”, few have attempted to explore the differences between contagion events in developing regions such as Africa and contagion events in developed markets. In this thesis I explore the possibility that any differences found might relate to differences in the extent of *financial linkages,* or *integration*, between the originating market and the contaminated market. In Section

---

1 Some elements of the materials in this chapter were originally submitted as part of my post graduate programmes. These relate to modules taken in respect to my Master programme, the critical review of literature and also annual performance review panel submissions for my PhD programme. These were all my own work and were submitted to Coventry University.

2.4, I therefore examine the literature for evidence of *differences* in financial market integration between developed and emerging markets. I lay a particular focus here on examining the literature from an African perspective.

There is a strong focus in the literature on explaining contagion from a behavioural-finance-related perspective. For this reason, in Section 2.5, I examine in detail the types of behavioural-finance-related decision biases that *may* potentially have roles to play in contagion events during a crisis or periods of uncertainty. Material from this section is used in Chapter 6 in my discussion of reasons for possible differences between contagion events from the US to developed markets and contagion events from the US to emerging/frontier African markets.

I believe that there is a possible relationship between the strength of financial linkages/integration between markets and the types of behavioural bias that may be observed during contagion events. For this reason Section 2.6 examines the literature for evidence of the relationship between market integration and observed biases.

Section 2.7 gives a detailed description of the different contagion methodologies or testing frameworks that are found in the literature (it should be noted that detailed analysis of the econometric issues is left to later chapters). This is done as part of the process of identifying the "gap in the literature" that my subsequent research will focus on. The section starts with a selection of papers to highlight the development of contagion literature and methodology in Section 2.7.1, before providing general evidences of contagion in Section 2.7.2.

This chapter concludes in Section 2.8 by identifying gaps in the literature and the research questions that will provide the basis of the thesis. The key focus identified is to examine the differences between contagion events in African markets and contagion events in developed markets. The novelty of the thesis is outlined in Section 2.8.

2.2 DEFINITIONS OF CONTAGION

Despite the growing literature on financial contagion, the term has no universally accepted definition. This is particularly seen in the different approaches adopted in testing for contagion effect. Rigobon (2001:4) expressed the agreement among economists on which one of the crashes (from 1982 to 2000) is a case of contagion. In his words, "paradoxically, on the other hand, there is no accordance on what contagion means". In the opinion of Caporale, Cipollini and Spagnolo (2005:477); "there is no consensus among economists on what constitutes contagion and how it should be defined. For instance, it is argued by some that it is necessary to identify exactly how a shock is propagated across countries and that only certain types of transmission mechanism (such as "herding" or irrational investor behaviour) constitute contagion".

The World Bank[2] (2013) proposes several definitions of contagion: the three key definitions proposed by the Bank are referred to as:

1. Broad definition
2. Restrictive definition
3. Very restrictive definition

Broad definition

"Contagion is the cross-country transmission of shocks or the general cross-country spill-over effects".

[2] The permanent World Bank URL for contagion definition is http://go.worldbank.org/JIBDRK3YC0.

Restrictive definition

"Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behaviour".

Very restrictive definition

"Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times".

Other definitions of contagion include:

1. Edwards (2000:879) reports that "Eichengreen and Rose (1999) and Kaminsky and Reinhart (1999) defined contagion as a situation where the knowledge that there is a crisis elsewhere increases the probability of a domestic crisis".
2. According to Dornbusch, Park and Claessens (2000:3): "Contagion is a significant increase in cross-market linkages after a shock to an individual country (or group of countries)".
3. Forbes and Rigobon (2002:2223) defined contagion effect as "a significant increase in cross-market linkages resulting from a shock hitting one country or group of countries", and described the terminology as "shift contagion". This definition has been accepted and cited by many researchers. Forbes and Rigobon (2002) explain that if markets exhibit high positive correlations during stable periods and follow suit after a shock hitting one market, these might not necessitate instances of contagion. A significant increase in the markets' co-movement (positive correlations) after a shock must be established to constitute contagion, otherwise continued high levels of correlations are attributed to the

strong linkages that exist between the markets. This situation is termed "interdependence" (Forbes and Rigobon 2002:2224).

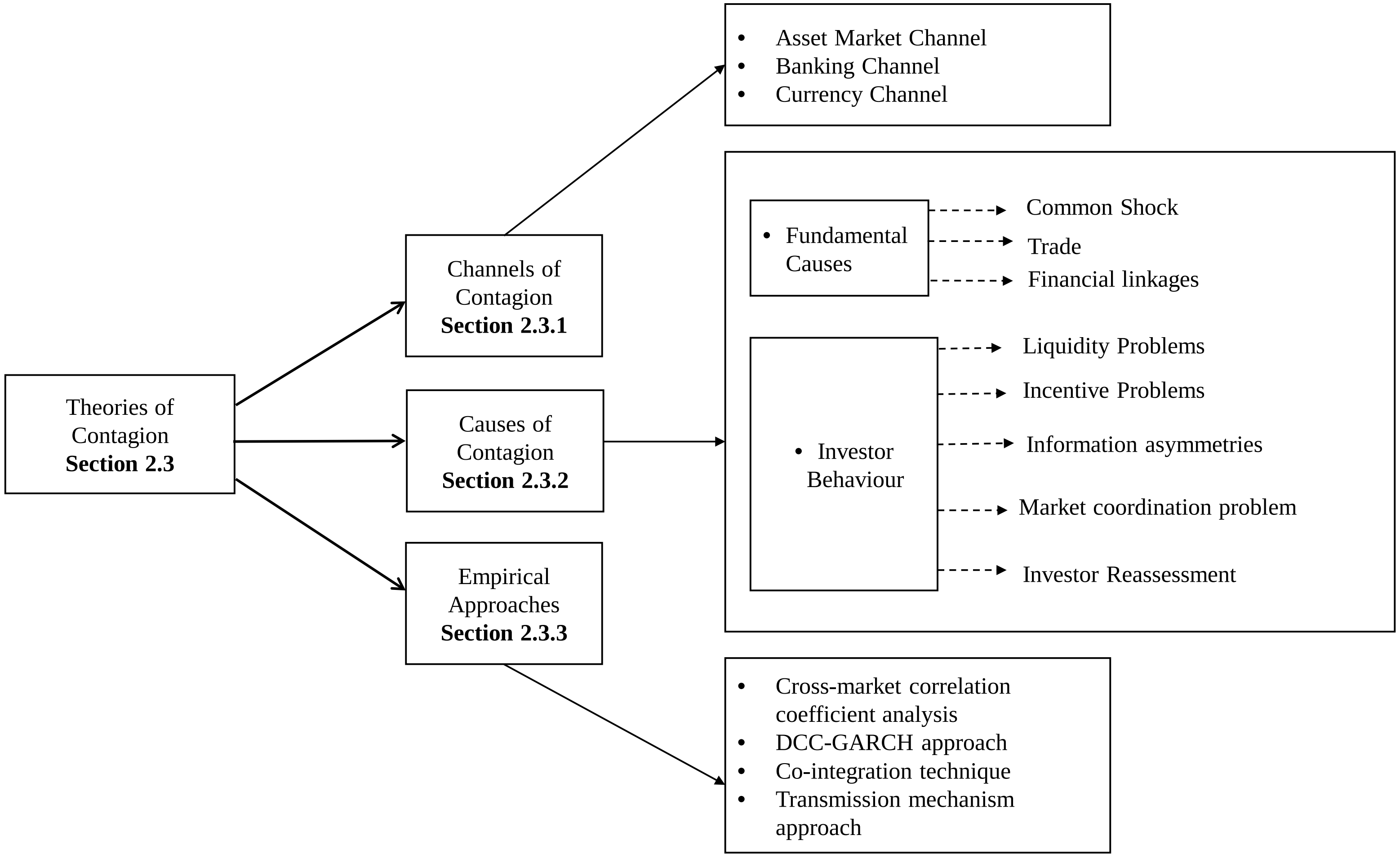
Often researchers classify contagion definitions into two: ***broad definition and narrow definition.***

4. In the opinion of Claessens and Forbes (2004), it is important to differentiate between the narrow and broad definitions. They assert that the broader definition is most preferred by government officials and policy-makers since it captures the exposure of one country to events occurring in other countries in spite of why that exposure occurs, whether or not those linkages exist at all times. Claessens and Forbes (2004) termed the narrower definition as "shift contagion". They explained that differentiating the definitions is important in measuring the effectiveness of interventions and rescue packages. In their view, a short-term loan could be effective to support a country and avoid contagion in terms of a shift contagion if, for example, a country is affected by the crisis of another but only for a short period of time provided there exist few linkages through trade, finance and other channels of transmission. In terms of the broader definition, where two countries are closely linked through trade and other financial linkages, a crisis in one country will require the other country to adjust to the shock. Government intervention in this situation except for other reasons would only lengthen the adjustment period.

2.3 THEORIES OF CONTAGION

The difficulty in identifying the precise definition of contagion has led to a wide variety of approaches in the literature. In this section, I begin by developing a cognitive map to identify how the different theoretical approaches relate to each other.

Figure 2.1: Cognitive map showing theories of contagion



Several theoretical explanations have been given on the existence of contagion. For instance, Masson (1998) has emphasised the multiple equilibrium theory where changes in investors' expectations or sentiments can result in the sudden shift of an economy from a good to a bad equilibrium. Calvo and Mendoza (2000) developed formal models where cost of information may lead investors to follow supposedly informed market participants, which will subject the market to rumours resulting in ***herd behaviour***. Consequently, this will create swings in financial variables even in countries with strong fundamentals.

There is also the theory of liquidity squeezes investigated by Valdes (1998), where international investors in a particular emerging country are faced with difficulties and decide to sell off their investments in the same asset class. As a consequence, there will be declines in asset prices in other countries that were not originally affected by the crisis and that have strong fundamentals.

Edwards (2000) classified contagion into three theoretical groups: multiple equilibriums, where changes in investors' expectations or sentiments occur; incomplete and/or asymmetric information, where information cost leads investors to follow other supposedly informed market participants; and liquidity squeezes, where international investors face difficulty in an emerging country which could lead to the sell-off securities in the same asset class.

Investigating the spread of a crisis across borders, Kaminsky, Reinhart and Vegh (2003) separate contagion theories into three groups – herding behaviour, trade linkages and financial linkages – and deduce that financial linkages and investor behaviour are the more prominent theories explaining contagion in their paper. Offering another theoretical explanation, Schmukler (2004) identified three classes of contagion theories: real linkages, financial linkages, and herd behaviour or unexplained high correlations.

The market condition problem is another way in which investor behaviour can cause contagion. Here, investor behaviour involves changes in expectations that are self-fulfilling in financial markets that can generate multiple equilibriums (Diamond, Douglas and Philip 1983, Obstfeld 1986). For instance, a crisis in an emerging market can cause another emerging market to jump from a good to a bad equilibrium. This type of investor behaviour even though it is individually rational can create volatility in financial markets (Dornbusch, Park and Claessens 2000).

The theoretical literature on financial contagion is vast and often tedious to deal with. To systemise it, the literature is discussed under the following categories:

1. **Channels of contagion:** This section helps to clarify the various channels through which crisis can be transferred from one market to another.
2. **Causes of contagion**: Another way of categorising the literature is in the way in which the crisis is transferred. The main two theories of contagion causes are fundamental causes and investor behaviour.
3. **Empirical approaches of contagion:** Contagion literature can be discussed by looking at the different methodologies adopted in analysing market co-movement. These are the testing frameworks employed in contagion studies. Section 2.3.3 gives an introduction to the testing frameworks. Further details are provided in Chapters 3, 4 and 5.

2.3.1 Channels of contagion

Huang (2000) identifies three channels of contagion, which he calls the ABC channels, meaning the asset market channel (see also Fry-McKibbin, Martin and Tang 2013, Galesi and Sgherri 2009, Beirne and Gieck 2012), the banking channel (Tonzer 2013) and the currency channel (Eichengreen and Rose 1999, Lau and Li 2001). These are the channels in which risk can be transferred from one market to another. Similar to Huang's (2000) work is the work of Pritsker (2001), who studied contagion through real sector linkages, financial market linkages and through the interaction of financial institutions and financial markets. More recently, Forbes (2012) reports that the channels of contagion can be categorised in terms of: (i) theoretical models (such as imperfect information, information cascade and compensation structures) and (ii) actors that cause contagion (such as banks and investors). Forbes (2012) decided to divide this categorisation into four channels. These are trade, banks, portfolio investors and wake-up calls.

For simplicity, the sub-headings below elaborate the categorisation of contagion channels according to Huang (2000).

A. ASSET MARKET CHANNEL

This channel of transmission focuses on contagion as a financial market phenomenon. King and Wadhwani (1990) explain this as a situation whereby changes in the price of assets in one market reveal imperfect information in the value of assets in other markets; not all information is publicly available or arrives at the same time and investor will judge on the information available from price changes in other markets. In light of this, contagion is perceived as rational attempts to use imperfect information about significant events to equity values. Extending the argument by King and Wadhwani (1990), Schinasi and Smith (1999) submitted that contagion does not necessarily depend on market imperfections; it can occur from portfolio diversification and leverage. Investor will sell off their high-risk assets provided that they are leveraged in order diversify their portfolio in response to a shock hitting one asset.

B. BANKING CHANNEL

The banking system channels explain how a run on one bank can lead to the subsequent collapse of other banks and the entire banking system. Most research on this theory seems to extend the seminal work of Diamond and Dybvig (1983); their research explains the vulnerability of banks to runs. The major problem leading to bank run is the imperfection of the interbank market resulting from information asymmetry or limited liquidity. Kaminsky and Reinhart (1998) examined the potential for contagion through exposure to a common lender. They found that common bank lenders have played a significant role in the spread of currency crises. Their study supports the theory that the banking channel outperforms trade channels in explaining the likelihood of countries to suffer from contagion effect.

Aghion, Bolton and Dewatripont (1999) reported that liquidity insufficiency in the domestic interbank market may result in contagious bank failures. If a bank run occurs, depositors will assume that their interbank market will not have enough liquidity to assist and will therefore start to run on their own banks. Huang and Xu (2000) on what they called the “lemon” problem explains that information asymmetry among banks trading in the interbank market could prevent banks with liquidity surplus from assisting other banks in trouble. With improvement in technology providing fairly reachable access to information, one might predict that information asymmetry among banks will be limited over time.

C. CURRENCY CHANNEL

The currency channel is one channel highly connected to the fast spread of crises in the Asian region in the late 1990s (Lau and Li 2001). After the Thai baht was devalued on 2 July 1997, crises were quickly sparked in Malaysia, Indonesia and other East Asian countries. Some researchers concluded that the crises led to contagion. Taketa (2004) studied contagion of currency crises across unrelated countries and found that currency crises can spread from one country to another even if their economic fundamentals are not related. Empirical evidence such as Jeanne (1998) reported that mismatch in international liquidity creates conditions for currency crises.

This channel of transmission is often related to the banking channel; as such, they are collectively referred to as “twin crises” (see Goldfajn and Valdes 1997). Pesenti and Tille (2000) explain that currency crisis adversely affects the banking sector when its liabilities are in foreign currency. In the event of devaluation, the value of the liabilities expressed in domestic currency increases; because domestic bank lending is normally in local currency, devaluation will expose the banks to a sizeable currency mismatch and a deterioration of their balance sheets. In a reversal, currency crisis can emerge through a burden imposed on the fiscal side of the economy by a banking crisis. Pesenti and Tille (2000:8) also submitted: “In the absence of common shocks, a currency crisis can be transmitted from one country (A) to another (B) if structural links and international spill-overs make the economies of countries A and B interdependent”. This channel is the most related to the financial crises of the late 1990s.

2.3.2 Causes of contagion

We have looked at different channels through which certain risks can spread contagion. One way of dealing with contagion literature, according to Claessens and Forbes (2004), is to classify the literature as the way contagion emerges. Claessens and Forbes (2004) classified the causes of contagion into two broad categories: fundamental causes (Kaminsky and Reinhart 1998) such as common shock, trade and financial linkages and, investor behaviour such as liquidity problems, incentive problems, informational asymmetries, market coordination problems and investor reassessment.

A. FUNDAMENTAL CAUSES

Bekaert, Harvey and Ng (2005) define contagion as excess correlation above what would be expected from economic fundamentals; they clearly identified the disagreement on what fundamental means, the nature of country-specific fundamentals and the link between fundamentals and asset correlations. In a more recent study, Ahnert and Bertsch (2014), "A wake-up call for theory of contagion", found that the reassessment of fundamentals increases the probability of a crisis in one region spreading to a second region. They defined contagion as an increase in the probability of a financial crisis in the second region after a crisis in the first region (Ahnert and Bertsch 2014:1). The main contribution of their study shows that contagion can occur after a wake-up call even where fundamentals are found to be uncorrelated. Their study follows Forbes (2012), who submits that common examples of contagion are "wake-up calls". Forbes (2012) explains that a crisis in one region is a wake-up call to investors in other regions, which leads to the reappraisal of risks. Investors reassess local fundamentals, resulting in financial crises in these regions. Both weaker fundamentals (due to the exposure to the initial crisis region) and merely an enhanced perception of risk about fundamentals are consistent with the notion of wake-up calls.

a. *Common shock*

Often referred to as global shock and sometimes the monsoonal effect, common shock can lead to excess co-movement in asset prices and capital flows (Dornbusch, Park and Claessens 2000). It is explained as a situation where a crisis in developed countries such as currency devaluation, interest rate changes, a change in commodity prices, and/or a reduction in global growth could generate crises in emerging countries and large capital outflows. A financial crisis may spread from one country to another as a result of some common shocks. For example, "a major economic shift in industrial countries (such as changes in interest rates or currency values), a change in commodity prices, and/or a reduction in global growth can trigger crises and large capital outflows from emerging markets. Any of these common shocks can lead to increased co-movements in asset prices and capital flows" (Claessens and Forbes 2004).

b. *Trade*

The likelihood of crisis transferring from the country of origin to another is very high with direct trade linkages. Reduction in income as a consequence of financial crisis will also lead to a reduction in the demand for imports off-setting the balance of trade by also affecting exports and related economic fundamentals in other economies. Trade linkages often lead to competitive devaluation among countries (Dornbusch, Park and Claessens 2000, Corsetti, Pesenti and Roubini 1999). For instance if crisis affects a country, forcing its currency to be devalued and thereby reducing the export competitiveness of other countries competing in the third market, its trading partners will also resort to devaluing their currency to maintain a balance (Dornbusch, Park and

Claessens 2000). Successions of competitive devaluation will, however, lead to large currency depreciations required by the initial deterioration in fundamentals. Hermandez and Valdes (2001) identified trade links and neighbouring effects as the most relevant channels of contagion during the Thai and Brazilian crises. An earlier study by Eichengreen and Rose (1999) emphasised the international trade channel as the financial transmission mechanism in advanced nations.

c. *Financial linkages*

Studies on financial crises and growing market integration are becoming more apparent in finance literature (see Wongswan 2003, Gilmore and McManus 2002, Patev and Kanaryan 2003, Bekaert, Harvey and Ng 2005). With growing market integration, the direct financing effect arising from the crisis of one country can be felt by other countries either through reductions in trade credit, foreign direct investment and other capital flows. For example, if country A supplies capital to country B, a crisis in country A will reduce capital supply in the form of bank lending and other forms of investment to country B (Claessens and Forbes 2004). Financial linkages are similar to trade linkages. It is demonstrated by Račickas and Vasiliauskaitė (2012:91) that "the debate on the relative importance of trade linkages versus financial flows continues to be unresolved. However, researchers agree that it is difficult to separate these two ways of financial contagion, because most countries that are linked in trade are also linked in finance".

B. *INVESTOR BEHAVIOUR*

Contagion can also be caused by factors other than fundamentals, as discussed above. In situations where there are no fundamental causes such as common/global shock, contagion is said to be caused by investor behaviour and other financial agents. For example, a crisis in one country might make investors in other countries withdraw their investments, ignoring the differences in economic fundamentals among countries. This type of contagion is strongly linked to herding behaviour (Dornbusch and Claessens 2000). "Although investor behaviour is often ex-ante, individually rational, it can still lead to excessive co-movements in market prices, in the sense that market prices are not explained by real fundamentals" (Račickas and Vasiliauskaitė 2011:1178). Identified below are five categories of investor behaviour that could cause contagion.

a. *Liquidity problems*

Liquidity problems are often associated with certain types of investors such as investors in hedge funds, open-ended fund managers and banks facing calls to margin (Claessens and Forbes 2004). This aspect of investor behaviour can cause prices outside the country/region of crisis to fall, making it possible for the initial crisis to escalate affecting different financial instruments, markets other than the original market of crisis and borrowers. Here, investors react to losses in one country by selling their securities in other markets to raise cash (Claessens and Forbes 2004). This kind of investor will usually keep the assets whose prices have fallen and have become less liquid and sell other assets in their portfolio. Emerging markets are also expected to be greatly affected with a liquidity problem because of their riskiness. For instance, banks could experience a decline in their loan quality to another country and decide to reduce overall riskiness of their loan portfolio by reducing exposure to high-risk investments, typically emerging markets (Claessens and Forbes 2004). Dornbusch, Park and Claessens (2000) made emphasis on this transmission mechanism with regard to emerging markets.

b. ***Incentive problems***

Another means of provoking contagion is through incentive structures and changes in *risk aversion*, where investors will sell their holdings in one market as a result of crisis in another to maintain certain proportions of a specific stock in their portfolios. In the same manner, an increase in risk aversion can cause investors to sell off assets with higher risk to closely track their benchmarks. This behaviour can cause tremendous decline in prices and even cause currency depreciation if similar benchmarks are used in evaluating a large number of investors, or if the investors own huge fixed currency in their portfolios (Claessens and Forbes 2004:7).

c. ***Informational asymmetries***

Emergence of contagion can also be caused by information asymmetries or the lack of perfect information (Claessens and Forbes 2004, Scardovo, Gatti and Ventola 2010, Račickas and Vasiliauskaitė 2011). Often, investors do not have a clear picture of the situation in another country that could affect the returns on their investment. Lack of adequate information can cause investors to think that the crisis of one country can be transmitted to other countries, or other countries might be having a similar crisis as well. As such, investors could sell their assets in other countries, especially those assets similar to the ones in the origin of the crisis, thereby causing contagion (Račickas and Vasiliauskaitė 2011). This type of investor behaviour could either be rational or irrational. In the presence of weak fundamentals, then investors could rationally assume that countries with related structures could face similar problems subsequently leading to contagion. Investor behaviour, however, is not only determined by the level of information available to them from other countries in their portfolio but also by information on the behaviours of other investors in other markets (Calvo and Mendoza

1998, Summers 2000, Crotty 2009, Račickas and Vasiliauskaitė 2011). Information is not often cheap to process; uninformed investors might find it cheap to follow the pattern of informed investors, adding more effects from informational asymmetries on investor behaviour (Claessens and Forbes 2004). “This type of herd behaviour may not only be an outcome of optimal portfolio diversification, but may also become more common as the fixed cost of gathering and processing country-specific information increases, the number of countries with investment opportunities grows and the range of investors widens. Also, with more diverse investors, establishing individual reputations becomes more costly, making it more likely that investors will follow the herd”. (Claessens and Forbes 2004:8)

d. *Market coordination problems*

Market condition problem is another way in which investor behaviour can cause contagion. Here, investor behaviour involves changes in expectations that are self-fulfilling in financial markets, which can generate multiple equilibriums. For instance, a crisis in an emerging market can cause another emerging market to jump from a good to a bad equilibrium characterised by currency devaluation, drops in asset prices, capital outflows or debt default. This kind of investor behaviour commonly occurs during a bank run. Diamond and Dybvig (1983) explain that this behaviour is individually rational among depositors; they could either hold funds or withdraw funds, depending on the action of all other depositors. The shift can either be bad for a bank if there is bank run, or good if depositors retain their money. In the outbreak of crisis, similar to what would happen in a bank run; depositors will quickly withdraw their money from another country as they fear that they might not be able claim a limited pool of foreign exchange reserve. Although this cause of contagion is regarded as one of the most general causes, it is hardly differentiated from fundamental causes because a shift between equilibriums could be caused by a jump in investor expectations; many factors are responsible for these jumps, which analysts argue appear to be fundamentals. Drazen (1999) reported that political factors may be associated with contagion during the European exchange-rate mechanism crisis. This type of investor behaviour even though it is individually rational can increase volatility and contagion in domestic financial markets (Dornbusch, Park and Claessens 2000).

e. *Investor reassessment*

Contagion may occur as result of investor reassessment. This is what Dornbusch, Park and Claessens (2000) referred to as “changes in the rule of the game”. Investors can change their assessment of the rules that govern international financing. The case of the Russian default in 1998 reflects a concern about other countries following similar unilateral policies on how foreign private creditors will be treated or the credibility of international financial institutions on bailouts during crisis. This could also lead to an increasing concern over the availability of supply of funds from international financing institutions such as the International Monetary Fund to assist countries facing a liquidity crisis. Dornbusch, Park and Claessens (2000) reported that the IMF aided several countries in late 1998, which raised concerns among economists whether it can cope with more liquidity crises. This theory of reassessment could lead to emergence of contagion. For instance, if an international financing institution lent to a country in crisis, other countries could fear there are insufficient funds to assist them during crisis, thereby triggering a run in those other countries; investors will sell off their assets in other countries outside the origin of the crisis. Shift in investor sentiment is more likely to affect a country with weak financial market fundamentals, usually from shocks that occurred elsewhere (Khalid and Rajaguru 2005).

2.3.3 Empirical approaches

Most of the methodologies[3] fall under the *broad*, *restrictive* or *very restrictive* definitions provided in Section 2.3 above.

Some of the empirical studies are based on unidentified channels of transmission such as the latent factor model, which originated from Sharpe (1964), and co-movement analysis, popularised by King and Wadhwani (1990) and later by Forbes and Rigobon (2002). Other studies focused on identifying various transmission channels of contagion leading to spill-over effects such as financial linkages or trade (Cheung, Tam and Szeto 2009). The most popular group of theories are those based on co-movement analysis with no identified linkages. Cheung, Tam and Szeto (2009) provided a summary of the empirical methodologies in Figure 2.2.

Figure 2.2: Summary of empirical methodologies of contagion

Source: (Cheung, Tam and Szeto 2009:8)

[3] See Dungey et al (2005a) for an extensive survey on the empirical methodologies of contagion.

Forbes and Rigobon (2002) identified four different methodologies for testing contagion and the international transmission of crises: 1) cross-market correlation coefficient analysis; 2) DCC-GARCH approach; 3) co-integration technique and 4) transmission mechanism approach. This categorisation is the most referenced classification in contagion literature. In a more recent paper, Forbes (2012) categorised the testing frameworks into five: 1) probability analysis; 2) cross-market correlations; 3) VAR models; 4) latent factor/GARCH models and 5) extreme value analysis.

Further methodological details on Forbes and Rigobon's (2002) classification are examined in Chapters 3, 4 and 5.

2.4 INTEGRATION AND FINANCIAL CRISIS

As I highlighted in the introduction to this chapter, differences in which contagion events spread throughout the world may, in part, reflect differences in the extent to which financial markets are linked/integrated. Differences in these relationships are explored in this section with a particular focus on US-African market relationships.

Waves of financial crises from the 1990s to the most recent in 2007-2009 affected both developed and developing countries globally. This strongly reinforced the debate on financial integration and globalisation (Schmukler 2004, Morales and Andreosso-O'Callaghan 2010, Mendoza and Quadrini 2010, Asongu 2011b, Mulyadi and Anwar 2012, Ozkan and Unsal 2012, Rose 2011, Inci, Li and McCarthy 2011, Račickas and Vasiliauskaitė 2012, Huang and Chen 2014). Schmukler (2004:39) offers this perception of globalisation and integration as: "Financial globalisation is understood as the integration of a country's local financial system with international financial markets and institutions. This integration typically requires that governments liberalise the domestic financial sector and the capital account. Integration takes place when liberalised economies experience an increase in cross-country capital movement, including an active participation of local borrowers and lenders in international markets and a widespread use of international financial intermediaries”. Schmukler (2004) further asserts that financial globalisation carries risks that are more likely to appear in the short run when countries open up, one such risk is financial crisis. This viewpoint is provided by Sinha and Pachori (2014:90): “The global market has given a lot to the economy of every country. But every growth and success comes with a cost so as the globalisation. The integration of various financial markets sometimes has resulted in financial crisis and contagion”.

Collins and Biekpe (2003:1) reported that: “When a market becomes financially integrated, companies can access a large new pool of investors. The cost of equity may decline and more investment projects are then viable. The result is increased growth and employment”. Collins and Biekpe (2003:2) further provided this perspective: “The downside to increased global integration is an increased exposure to global crises. If a country is highly integrated with global markets, their financial market may suffer a dramatic market downturn that may or may not be related to that country’s own sovereign risk. Open capital accounts and increased global market integration then seem to be a mixed blessing. The positive implications of cost of capital and growth are counterbalanced by vulnerability to global economic events. Economic crises usually have damaging effects on economic growth and stability. The spread of a crisis would then depend heavily on the degree of financial market integration, that the more integrated markets are, the higher could be the contagious effects of a shock to another country. Countries that are less financially integrated, either by capital controls or the lack of access to international financing, should then be relatively immune to contagion".

Schmukler (2004) submitted that countries around the world have become more integrated, driven by the potential benefits of financial globalisation such as financial sector development. The crises of the 1990s after many countries have liberalised raised the question of gains from globalisation; the downside is that countries become more exposed to contagion effects from other countries.

Claessens and Forbes (2004) and Račickas and Vasiliauskaitė (2011) are of the opinion that countries are likely to be linked together through periods of weakness or strength as financial integration increases around the world. Kassim (2013:80) reports that "a review of studies reveals the time-varying aspect of stock market integration and indicates that the nature of stock market integration changes due to financial crises. Essentially, stock markets tend to move in unison during a down market but exhibit low integration during normal times". For instance, Cuñado, Gil-Alana and Perez de Gracia (2008), tested stock market volatility in the US during bull and bear phases. The study estimated the order of integration in the squared returns in the S&P 500 over the sample period August 1928 to December 2006. The results suggest that in many cases volatility is more persistent in the bear market than in the bull market. Tuluca and Zwick (2001) studied the effect of the 1997 Asian financial crisis on 13 international stock markets and found increased feedback relationships between the stock markets post the financial crisis. Cheng and Glascock (2006) investigated stock market linkages between the US and three Asian stock markets (China, Hong Kong and Taiwan) before and after the Asian financial crisis of 1997. They found increased feedback relationship between the markets after the crisis. Earlier, Hon, Strauss, and Yong (2004) tested for contagion after the terrorist acts in New York and Washington on 11 September 2001. They showed that European markets in particular responded more closely to US market shocks in the three to six months after the terrorist attack.

Kang and Yoon (2011), in their study “The Global Financial Crisis and the Integration of Emerging Stock Markets in Asia”, examined whether the global financial crisis of 2008 has increased the integration of the Chinese stock market with other emerging stock markets in Asia. The markets studied are China, Hong Kong, Korea, Singapore and Taiwan. The findings of Kang and Yoon (2011) suggest that the 2008 financial crisis increased the integration of the Chinese stock market into Asian stock markets. The strengthening of this integration implies limitation to international gains from equity portfolios.

Kassim (2013) investigated the impact of the 2007 financial crisis on the integration of Islamic stock markets in: Indonesia- Jakarta Islamic Stock Index (JAKIS); Kuwait-Dow Jones Islamic Index of Kuwait (DJIMKW); Malaysia- Dow Jones Islamic Index of Malaysia (DJIMY); Turkey- Dow Jones Islamic Index of Turkey (DJIMTR); Japan-Dow Jones Islamic Index of Japan (DJIJ); UK- Dow Jones Islamic Index of the UK (DJIUK) and the US- Dow Jones Islamic Index of America (IMUS). The study covers the period 9 January 2005 to 10 January 2010, divided into pre-crisis and crisis periods. Their findings suggest that the Islamic stock markets studied are not fully sheltered from the global financial crisis. However, it is observed that the impact of the crisis on the Islamic stock markets has not been as severe as it has been on the conventional stock markets. It is also found that Islamic stock markets in developing countries provided higher average returns compared with their counterparts in developed countries. Analysis of the integration of the markets during the crisis suggests that all of the Islamic stock markets are interrelated in the long run. The author suggests that it can be explained by the structural similarity produced by the requirement to observe Islamic laws. The author concludes that in the non-crisis period, investors can gain from portfolio diversification by considering both developed and developing countries' Islamic stock markets in their investment portfolios.

In terms of mainly the benefits of international portfolio diversification (Longin and Solnik 1995, Harvey 1995, Errunza 1994), there are many studies that deal with emerging stock markets, which are said to have lower exposure to world factors, hence lower levels of integration. Therefore, they may offer greater opportunities for risk diversification across countries. A study by Errunza (1994), suggests that emerging markets still offer international money managers opportunities to diversify risk and seek higher returns. Harvey (1995) explains that part of the reason why emerging markets were a viable asset class in the early 1990s was due to their low correlation with developed markets, which enables them to serve as a hedge in a global portfolio. However, Harvey (1995) pointed out changing correlations between emerging markets and developed markets, as emerging markets become integrated into the global financial system. More recently on diversification, Ampomah (2008), in "An empirical examination of the interlinkages between African stock markets", provided evidence that African stock markets are still segmented from global markets, offering strong diversification benefits.

2.4.1 Integration from Africa's perspective

While financial market integration has been extensively documented in developed countries and emerging Asian countries, the integration of Africa's emerging and frontier stock markets has received little attention in the literature. Few African markets have been included in extensive research (see Harvey 1995, Mobarek, Muradoglu and Mollah 2014), especially in the 1990s and early 2000s. This is expected given the size, illiquidity and erratic nature of the markets. However, the degree of integration of some African markets into global financial markets tends to change over time as a result of increased liberalisation and efforts to promote integration of these markets into the global economy. Still, researchers such as Hatemi-J and Morgan (2007) in their study of 17 emerging markets including Nigeria and Zimbabwe found that the liberalisation efforts of the markets towards the world market appear insignificant. The Nigerian and Zimbabwean markets, in particular, are less globally integrated. Pukthuanthong and Roll (2009) found that integration has improved in South Africa, Mauritius and Egypt but declined in Ghana, Nigeria and Zimbabwe.

Bekaert et al. (2011) studied segmentation in equity markets. They found that the US, Australia, UK, Switzerland and Denmark are the least segmented countries, while Ghana and Ivory Coast (Côte d'Ivoire) are the most segmented emerging markets in their sample. Berger, Pukthuanthong and Yang (2011) analysed frontier market equities with respect to world market integration and diversification. They found little evidence of integration in some African countries including Kenya, Mauritius and Nigeria, whereas Botswana, Ghana, and Tunisia exhibit some level of positive world market integration. Also on integration of African markets, Agyei-Ampomah (2011) found that African stock markets except South Africa are still segmented from global markets despite recent structural improvement. They also found low correlation between the African markets themselves, for example, the markets within the ECOWAS bloc: these are Nigeria, Ghana and Ivory Coast (Côte d'Ivoire). Agyei-Ampomah (2011) also found that the markets experienced time-varying integration that has diminished over time making the markets more segmented in recent times.

Boamah (2014) investigates the integration of 11 African markets relative to the world and emerging markets over the period March 1997 to January 2013. Boamah's sampled countries include; Botswana, Ivory Coast, Egypt, Ghana, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia and Zambia, Africa value weighted and Africa equally weighted. The study shows a stronger relationship between South Africa and the world market compared with other African countries, which implies that South Africa is the most accessible and integrated market in Africa. The findings also support the hypothesis of partially integrated African markets relative to the world and emerging markets and that the integration of African markets has changed through time.

2.4.2 Conclusions: the integration of African markets with the US

Despite the growth of African stock markets, they are still generally perceived to be weakly integrated with developed markets. The question arises:

- Were emerging African markets shielded from the crisis because of their low integration with the US? OR
- Did correlations with African markets increase to the extent that it can be described as a contagion event?

In this thesis, I argue that the impact of the 2007-09 crisis can be characterised in terms of its differing impact on correlations with the US and (i) highly integrated markets and (ii) low-integrated markets.

Highly integrated markets will refer to markets closely related to the US. These are likely to be the developed country markets such as Canada, the UK and Germany.

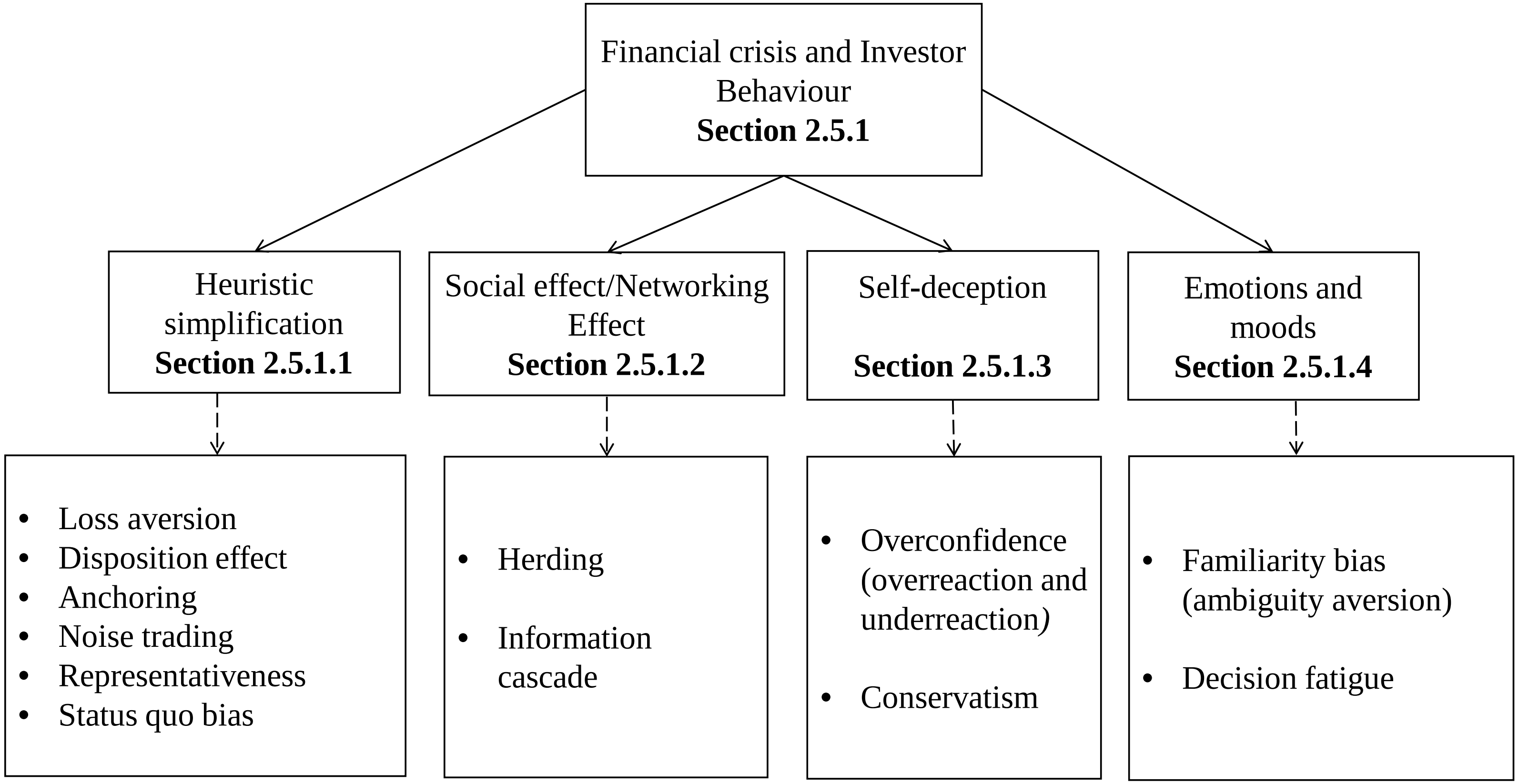
Low-integrated markets, on the other hand, will include low-growth emerging markets or frontier markets. These are represented by African markets in this thesis.

2.5 INVESTOR BEHAVIOUR: A BEHAVIOURAL FINANCE PERSPECTIVE

In the introduction to this chapter, I argued that differences in levels of financial integration between markets could possibly result in contagion events manifesting themselves in terms of different behavioural-finance-related decision biases. Bearing this in mind, in this section I examine in detail the types of decision biases that could *potentially* manifest themselves in contagion events. Elements of these will then be used in Chapter 6 in my discussion of differences in the nature of contagion between the US and African markets and contagion between the US and developed markets.

This section will focus on the impact of behavioural biases on investor behaviour and the structure of the academic literature can be summarised through the following cognitive map.

Figure 2.3: Cognitive map showing behavioural biases in stock markets



2.5.1 Financial crisis and investor behaviour

Evanoff, Kaufman and Malliaris (2012), submit that bursting of asset price bubbles have generated turmoil in financial markets and the wider economy. It can be argued that these bubbles are consequence of behavioural biases in investor behaviour.

An economy bubble has been identified in financial crises as the most important origin of an economic crisis. Popular crises preceded by bubbles include the: Tulip Mania of 1634 to 1637 in the Netherlands (Garber 1989, Thompson 2006, French 2006, Malkiel 2010); the South Sea Bubble of 1716-1720 in Britain during the 18th century (Garber 1990, Thomas 2003, Carswell 1960, Malkiel 2010, Frehen, Goetzmann and Rouwenhorst 2011); the Mississippi Bubble of France also in the 18th century(Garber 1990, Irving 2008, Theirs 1859); Japan’s Bubble Economy of the 1980s (Okina, Shirakawa and Shiratsuka 2000, Barsky 2009, Ishikawa 2011, Shimizu and Watanabe 2010, Malkiel 2010); the dot-com bubble in the 1990s in the US (Kraay and Ventura 2007, Malkiel 2010); the stock market crash of October 1987 (King and Wadhwani 1990, Fortune 1993, Shiller, Konya and Tsutsui 1988 and, Yang and Bessler 2006). Citing these past crises, one could describe the stock market fall of 2007-2009 across the globe as a speculative bubble crash developing from the housing bubble experienced in the late 1990s and early 2000s in the US.

Lin, Dinh and Im (2010:23) have this viewpoint: “But how did the financial crisis in the United States spread over to other advanced countries? In order to understand this, first we need to note that the credit boom in the years preceding the crisis was not only limited to the United States but also to other advanced countries as well. Many of these conditions, for example, low credit risk and spreads, very high asset and housing prices pre-existed worldwide. On the other hand, many non-US financial institutions invested heavily in subprime backed securities and other complex derivatives. When the housing bubble in the United States burst, other advanced countries were not able to escape the financial turmoil due to the linkages in the financial sectors. Moreover, ***uncertainty*** over the exposure of other financial intermediaries further exacerbated the credit crunch in other advanced countries".

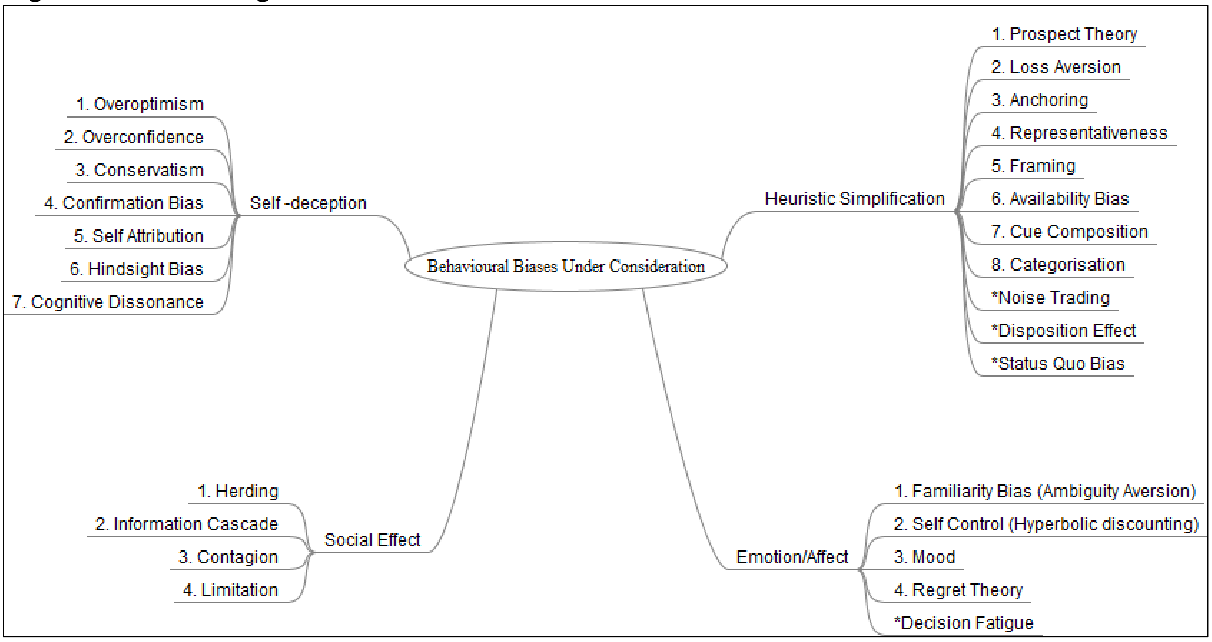
Behavioural finance literature has documented many behavioural biases that affect decision-making especially during periods of uncertainty, as experienced during the 2007-09 financial crisis. For instance, one of the most popular and well-documented behavioural explanations for the existence of variability and short trends in financial market is the herding behaviour of both individual and private investors.

Behavioural finance can be described as cognitive psychology and limits to arbitrage (Ritter 2003). A number of biases from both cognitive psychology and limits to arbitrage influence decision-making. Although this area is fairly new and still evolving, its contribution to market behaviour is quite reasonable.

The four main categories of psychological factors identified by researchers such as Hirshleifer (2001:1533-1597) are presented in Figure 2.4 below. The biases[4] that are more prominent in financial markets are then individually discussed below.

[4] Note that studies have identified more than 100 behavioural risk indicators that affect decision-making (See, for example, Ricciardi, 2008). This thesis focused mainly on indicators related to financial markets as reported in several literatures. Biases preceded by an asterisk are not identified by Hirshleifer (2001).

Figure 2.4: Showing behavioural biases in stock markets



2.5.1.1 Heuristic simplification

"Heuristic simplification arises from the limitations of people's cognitive powers (such as memory and thought). It involves the process of using shortcuts to deal with complex decisions. *Rules-of-the-thumb* are examples of heuristic simplification. Such short cuts can produce a tainted perception of the situation being thought about" (Redhead 2008:26). Heuristic simplification is sometimes referred to as information processing errors. When individuals face complex situations such as statistical probability, frequency or incomplete information, they utilise a limited number of heuristics to reduce the decision to a simpler task (Kahneman, Slovic and Tversky 1982). In the opinion of Myers (1989:286), "all of us have a repertoire of these strategies based on bits of knowledge we have picked up, rules we have learned or hypotheses that worked in the past". Plous (1993:109) submitted that: "For example, it is easier to estimate how likely an outcome is by using a heuristic than by tallying every past occurrence of the outcome and dividing by the total number of times the outcome could have occurred. In most cases, rough approximations are sufficient (just as people often satisfice rather than optimise)". In other words: "Heuristics are mental shortcuts or strategies derived from our past experience that get us where we need to go quickly, but at the cost of sending us in the wrong direction" (Ricciardi and Simon (2001:19). Further biases under heuristic simplification are discussed below.

Prospect theory

The prospect theory is a mathematical alternative to the theory of expected utility maximisation. It is advocated under conditions of risk-taking behaviour and uncertainty. The theory was developed by the seminal work of Kahneman and Tversky in 1979. It is noted by Olsen (1997: 63) that the theory "gives weight to the cognitive limitations of human decision-makers", (in Ricciardi 2008:98). Under the assumptions of prospect theory, Thaler and Johnson (1990) found that when faced with chronological gambles, investors prefer to take risk if they will make money on initial gambling than if they lose. Kahneman and Tversky (1979) explained that this theory is based on the notion that people are loss-averse, in that they are more concerned with losses than gains. Investors' interpretation of this theory is assigning more significance to avoiding losses than making gains.

The major foundation of the prospect theory is the value function of Kahneman and Tversky (1979), illustrated in Figure 2.5 below. The figure is a hypothetical value function of wealth based on a reference point that determines the subjective impression of individuals. If wealth levels fall under the reference point, the function will be upward-sloping but if wealth levels fall after the reference point, the value function will be downward sloping. The reference point is the comparison level of individuals. For instance, people who are not risk-averse will make risky betting to stay above their preferred intended level of wealth.

Figure 2.5: A hypothetical value function of prospect theory

This image has been removed due to third party copyright. The unabridged version of the thesis can be
version of the thesis can be viewed at the Lanchester Library, Coventry University

Source: Kahneman and Tversky (1979)[5].

The important result of Kahneman and Tversky's (1979) work is that it demonstrates people's attitude towards risks and gains, as it is different from the risk of making a loss. "Investors treat outcomes as losses or gains from a subjective reference in two aspects: (1) people are risk-averse with their investments which are performing well (that is, investment gains) and as a result they have an inclination to cash in their profits too early and (2) individuals are risk-seekers for losses (that is, loss-averse) and in order to avoid a realised loss they will take a gamble (by avoiding to sell the asset) that could result in an even greater loss (Ricciardi 2008:99)". Further biases related to this theory include mental accounting, regret and loss aversion.

[5] The arrow showing the reference point is added by the author of this work.

Loss aversion

Kahneman and Tversky (1979) explained loss aversion under the prospect theory. It shows how decision-makers behave when faced with the issue of choice under uncertainty. The theory observes to see if people feel more pain for what they lose than pleasure with an equivalent gain, (Rabin 1998, Shalev 1996). Ang, Bekaert and Liu (2005) and Fielding and Stracca (2007) suggest that the reference point could change over time with the result that loss aversion is accompanied by disappointment aversion. "Under loss aversion, an investor has a fixed reference point, which might be the current level of stock prices or the current value of personal wealth. Gains and losses are evaluated under the reference point (Redhead 2008:37)". Also from Redhead (2008:37): "In the case of loss-aversion the pain of losses exceeds the pleasure of gains, when the gains and losses are of the same magnitude. In the case of disappointment aversion the pain or pleasure is brought about by deviations from expectations. The disappointment related to outcomes below expectations is stronger than the pleasure related to outcomes that exceed expectations". The value function in Figure 2.5 above shows the sharp asymmetry relationship between the importance investors put on gains and losses.

Loss aversion explains the inclination investors have towards retaining losing stocks while selling the stocks that are making gains too early. Shefrin and Statman (1985:778) called this investor behaviour the "*disposition effect*". Scott, Stumpp and Xu (1999) explains that risk in losses will make investors hold onto the stock for too long even when the price declines, thereby causing the price of the stock with negative momentum to overstate its fundamental values. In conclusion, if we view loss aversion in the context of the 2007-09 financial crisis, we would expect that investors might take a long time before they react to the crisis in the form of contagion effect.

Disposition effect

Shefrin and Statman (1985) suggested the disposition effect. This is explained by investors' attitude to sell stocks that have gained in value and hold unto those that have lost in value. The disposition effect is found to be consistent with the prospect theory of Kahneman and Tversky (1979), which suggests that investors choose a value as a reference point and make decisions based upon gains or losses from that value. As explained above, the prospect theory requires investors to be risk-averse concerning gains, but risk-seeking concerning losses.

Odean (1998a) found evidence of the disposition effect in all months except December when examining the reluctance of investors in realising their losses. Furthermore, Odean (1999) concluded that excessive trading behaviour of investors' is a result of the disposition effect. More recently, Barber et al. (2007) found evidence of the disposition effect in the Taiwan Stock Exchange, where investors are more likely to sell stock showing gains than those showing loss, although institutional investors, in particular in mutual funds, did not show evidence of the disposition effect.

Anchoring

Anchoring is made popular in behavioural finance literature from the work of Tversky and Kahneman (1974). This is a phenomenon whereby people's decisions are highly influenced. Redhead (2008:27) reports: "People are heavily influenced by past or suggested prices when forming judgements about appropriate prices. The past or suggested price acts as an anchor that becomes the basis for forming a judgement". According to Ricciardi and Simon (2001), anchoring explains the strong inclination we all have for holding on to a belief that may or may not be truthful and using it as a reference point for future decisions.

Shiller (1998:9) reported: “Values in speculative markets, like the stock market, are inherently ambiguous. Who would know what the value of the Dow Jones Industrial Average should be? Is it really ‘worth’ 6,000 today? Or 5,000 or 7,000? Or 2,000 or 10,000? There is no agreed-upon economic theory that would answer these questions. In the absence of any better information, past prices (or asking prices or prices of similar objects or other simple comparisons) are likely to be important determinants of prices today”.

In Shiller’s (2008) opinion, “the anchoring phenomenon may help to explain certain international puzzles observed in financial markets”. For example, in the late 1980s, US investors who thought that the Japanese stock price-earnings ratios were shockingly high may have been influenced by the readily available anchor of US price-earnings ratios, which are much lower. However, in the mid-1990s, many US investors felt that the Tokyo market was no longer overpriced, though the price-earnings ratios remained higher than the US (Shiller, Kon-Ya and Tsutsui 1996). This is attributed to the widely publicised high Tokyo price-earnings ratios of the late 1980s, which appear to be the anchor in this case.

Applying the concept of anchoring to the recent financial crisis, it can be described as the situation where market participants have become used to the crisis as it develops and they anchor on their initial position. As such, people are not making any effort to explore the market and therefore reductions in trading could be expected. This will subsequently lead to a reduction in correlation after the initial increase.

Noise trading

Fischer (1986) divides traders into information traders (those who use relevant information) and noise traders. In financial market literature, noise is referred to as immaterial information on market prices causing them to depart from their true values. Shefrin and Statman (1994) suggest that information trading is driven by the fundamental values of stocks as well as securities, while noise trading is driven by sentiment. In other words: “Noise trading is trading based on sentiments rather than market fundamentals, and such trading can cause stock prices to deviate from fundamental values for long periods of time” (Redhead 2008:249). Redhead (2008:545) also reports that Barberis, Shleifer and Vishny (1998), “suggested that noise traders, as a result of misinterpretation of information, see patterns where there are none”. Investors who have no access to inside information in the stock market act irrationally on information provided through noise trading. This can lead to herd behaviour when investors operate as a crowd.

Research has shown that noise traders have a substantial impact on price movement. For instance, bullish noise trading can push prices higher as fundamental values fall while bearish trading can push prices down even when fundamental values increase. Noise traders make use of irrelevant information such as rumours to draw investment decisions. Rumour is highly vindictive as professional traders fall prey. If trading on rumours is regarded as noise trading, then market professionals are sometimes noise traders. Pressure to act speedily prompts anxiety and stress, which leaves people vulnerable to accepting the rumour. For instance, competent professionals might not have time to check for the accuracy of rumours. As such, they might engage in noise trading (Redhead 2008). Rumours emerge in conditions of uncertainty, which is quite often in the financial market in particular when emotions, especially feelings of fear, are high (Kimmel 2004).

Representativeness

The representativeness heuristic is one of the characteristics of intuitive probability, identified by Tversky and Kahneman (1974) which explains the possibility of investors to track the market. In the opinion of Redhead (2008), representativeness helps in explaining why many are found to extrapolate price movements. Investors tend to believe that if prices have been rising in the past, then they will continue to rise. If, on the other hand, prices have been falling then they will continue to do so. Redhead (2008) further elaborated that the concept of representativeness suggests that investors see investments with a current rise in price as a representative of long-term successes and those with price falls as a representativeness of losses. This explains a pattern of trading where investors buy when prices are rising, thereby causing further price rises, and sell when prices are falling and the momentum makes prices fall further. Representativeness explains the emergence of opinions on price trends and through affecting trading those opinions become self-fulfilling. Determination of such opinion results in bubbles or crashes that can be explained by conservatism (where people are unwilling to change their opinion in the light of new information) and confirmation biases (where people pay attention only to information that supports their opinions).

“Human beings utilise mental shortcuts that make it complicated to analyse new investment information accurately without bias. Representativeness reflects the belief that a member of a category (for example, risky behaviour or hazardous activity) should resemble the cause that produced it” (Ricciardi 2008:100). Earlier, Ricciardi and Simon

(2001:21) purported: “Representativeness is but one of a number of heuristics that people use to render complex problems manageable. The concept of representativeness proposes that humans have an automatic inclination to make judgements based on the similarity of items, or predict future uncertain events by taking a small portion of data and drawing a holistic conclusion”.

Representativeness bias has the tendency to make people see patterns in a random data and feel comfortable about the pattern. Cooper, Dimitrov and Rau (2001) investigated the companies with.com or.net added to their names between June 1998 and July 1999 (the period of the internet stock bubble). They found that investors saw companies with.com or.net in their names as representative of prospective companies.

Another psychological bias closely related to representativeness is narrow framing. When investors focus on short-term investment, they are said to be narrow framing. For instance, investor might chose to ignore the current behaviour of share prices because it is centred on long-term investment. Redhead (2008:550) reports that: “This is consistent with the emergence of stock price bubbles and crashes. Recent price increases cause expectations of future increases and investors buy shares. This pushes prices up further, and hence generates an expectation of more increases and leads to yet more buying. There is an upward spiral, often referred to as positive feedback trading or ‘chasing the market’. There is a corresponding, but opposite, pattern as the market falls”.

Status quo bias

Samuelson and Zeckhauser (1988) observed the existence of a status quo bias (also known as an endowment bias). People have a tendency to maintain the investments they already have and exhibit some reluctance to change them regardless of changes in their environment. Status quo bias increases as the number of investment options increases. "In sum, status quo bias is pervasive. It is a natural consequence of many well-known psychologically based deviations from the rational choice model. As a result the canonical choice model is unlikely to provide a reliable explanation for a substantial range of behaviour, including economic behaviour" (Samuelson and Zeckhauser 1998:41). Samuelson and Zeckhauser (1998) identified further biases that will make people feel the status quo bias. These include regret avoidance, drive for consistency, self-perception theory and illusion of control. However, these biases are not necessarily present at the same time to generate the status quo bias.

In their experimental test on behaviour in a simplified stock market, Brown and Kagel (2009) tested for status quo bias, the disposition effect and the ostrich effect. Their experiment found a robust status quo bias across individuals, over time and independent of a stock's performance. They assert that status quo bias is present in an environment with a very low cost of identifying better performing stocks.

2.5.1.2 Social effect/Networking Effect

Social effects produce biases from social influence. The degree to which a person is influenced by the actions and thinking of others is related to a number of social factors (Schachter et al. 1986). "Social influence is strongest in conditions of uncertainty and when self-confidence is low. It is also strong with substantial changes in circumstances, and rises with the extent that previously held views are demonstrated to be incorrect" Redhead (2008:32).

In an earlier experimental work, Asch (1952) found that people are inclined to follow others even if they felt that the people they are following are wrong. He referred to this behaviour as “conformity”. Shiller and Pound (1989) found that when investors pay attention to a stock, often more than 50% of the time it is because another person mentioned the stock to them. And before buying the stock, the investor is also likely to speak about the stock to others. Smith (1991) identified “social influence”, which may imply following the leader. Social influence could be stronger when there is the feeling of uncertainty and when individuals find no direct personal experience. Social effect is strongly associated with networking effect. For instance, those who are well connected in a social network will be listened to by numerous other people; this gives the well connected people social influence. Social influence itself is affected by other characteristics such as status, expertise and social mood. The combination of these features can be described as socionomics (Redhead, 2008).

Herding

Herd entails “everybody doing what everyone else is doing even when their private information suggests doing something quite different” (Banerjee 1992:798). Redhead (2008) explains that when uniformity exists concerning the market’s direction, there is the likelihood that there will be market movement towards that direction. However, herding could be quite slow and persistent, thereby causing some stock market bubbles to take years before developing (Hwang and Salmon 2007). “Speculative bubbles, like those seen in the NASDAQ into 2000, the real estate market into 2006, the stock market into 2007, and the commodity markets into 2008, such bubbles are clearly not the result of independent, objectives, and rational investors’ research on new fundamental developments. Such bubbles are the result of herding behaviour. Behavioural economists defined such behaviour as a social contagion of emotions causing collective euphoria or fear” (Mackay, United-ICAP 2011:4).

Furthermore, the theory of herding distinguishes between different types. For instance, Bikhchandani and Sharma (2001:281) separate herding into intentional (sentiment driven) and unintentional or spurious herding (fundamental driven). They explained that spurious herding, for instance, could arise as a reaction to sudden increase in interest rates which results to stocks becoming less attractive investment. In such situations, investors might prefer to hold small percentage of stocks in their portfolio indicating that investors are reacting to the common public information on interest rates increase. Intentional herding on the other hand reflects the imitation of other individuals which results in buying or selling of stocks irrespective of previous information (Kremer 2010). According to Bikhchandani and Sharma (2001:283), intentional herding could be caused by "informational cascades, reputation-based herding, or the compensation systems for the portfolio managers". In a similar fashion Lutje and Menkhoff (2003:5) reported 3 reasons of intentional herding: "Imperfect information in markets where participants deliberately copy others assuming the others have relevant news about investment; Individual's inherent preference for conformity and; asset managers face incentives for reputational herding due to their typical compensation scheme".

Although the distinction between intentional and unintentional herding is very important, Bikhchandani and Sharma (2001:281) assert that empirical distinction between the two is "easier said than done and may even be impossible, since typically, a multitude of factors have the potential to affect an investment decision". For instance, Kodres and Pritsker (1996) examined the intensity of herding using probit analysis. The authors made no distinction between intentional and unintentional herding. However, researchers such as Kremer (2010) found evidence of unintentional herding from their data on the German DAX 30. Kremer (2010) attributed this finding to the sharing of the same preference and investment style as supposed to less information availability or information asymmetry. Blasco, Corredor and Ferreruela (2011) tested intentional herding behaviour of market participants in the Spanish stock market. They first analysed the whole market and a selection of large trading volume stocks, then they analysed heavily traded stocks using both intraday data and daily data. They found out that the Spanish market, especially the heavily traded stocks exhibit tendencies consistent with imitation. They further submitted that intentional herding is better revealed using intraday data instead of overall market data and lower frequency data. Other papers which focused on intentional and unintentional herding behaviour include: Walter and Weber (2006); Malik and Elahi (2014); Holmes, Kallinterakis and Ferreira (2011).

Herding among fund managers has been importantly and extensively documented because of the important role institutional investors have on the performance and development of stock exchanges. Lakonishok, Shleifer and Vishny (1992) carried out a study on quarterly portfolio holdings of 769 tax-exempt equity funds in the United States and reported that, in their sampled portfolio holdings, fund managers do not show evidence of significant herding behaviour. However, they found evidence that herding could be more common in stocks of small companies than those of large companies. Henker J., Henker T. and Mitsios (2003) described herding as an intraday phenomenon. They explained that on the release of information into the market, traders being unsure of what line of action to take may turn to each other. At intraday levels, traders cannot make rational decisions because they lack the time to seek complex models in predicting future price movement. Rational individuals are not immune to this herd-like behaviour when they take into account the judgements of others. Although it looks like a rational behaviour, it creates a group behaviour that is irrational and causes market fluctuations. Investors with no right to inside information act irrationally on noise as if it were a useful piece of information (Thaler 1993).

In financial contagion literature, herding behaviour seems to be generally accepted as a major cause of contagion (Kaminsky, Reinhart and Vegh 2003, Edwards 2000, Claessens and Forbes 2004). Information asymmetry stands at the root of herding behaviour, where information becomes costly and investors have to rely on other supposedly informed market participants (Edwards 2000). Additionally, investor behaviour could also be determined by information about the behaviours of other investors in other markets (Claessens and Forbes 2004). Other cognitive biases are also found to result in herding behaviour during a crisis or periods of uncertainties. These include information cascade and noise trading.

Information cascade

Cipriani and Guarino (2010) explained this bias as a situation where market agents do not use their own private information and herd, and that it can spread from one market to another causing financial contagion. To demonstrate this bias, they studied an economy in which privately informed traders' trade information with a market maker. They assert that traders trade for two reasons: (1) an information advantage over the market because of private information and (2) they gain from trading. Their finding suggests that as trades accumulate, the gains derived from trade overwhelm the informational advantage. As a consequence, traders act independently of information on the asset value, creating an information cascade. In the event of information cascade, all informed traders do the same thing. That is they herd by following the market, or go against the market resulting in contrarianism.

Cipriani and Guarino's (2010) study focused on correlated assets, as informational spill-overs are expected in such assets. Information cascade in one market can cause a cascade in another, thereby pushing prices even in the long run away from fundamentals. Cipriani and Guarino (2010) described the long-lasting spill-over as a form of contagion.

2.5.1.3 Self-deception

"Self-deception is the process whereby people exaggerate their abilities. They think that they are better than they really are" (Redhead 2008:24). Self-deception is also identified by Redhead as a bias that can be distorted by memory and planning. "Self-deception is a trait that some evolutionary theorists believe was actively selected for when humans were evolving. The argument is that sometimes it is easier for an individual to deceive others if he genuinely is fooled himself" (Coval, Hirshleifer and Teoh 2004:6). The most popular biases under this are the overconfidence bias, conservatism bias, the hindsight bias, optimism or self-enhancement bias, outcome bias, confirmation bias and illusion of control. Overconfidence and conservatism are discussed below.

Overconfidence

In the opinion of Daniel and Titman (2000), overconfidence is one of the most documented biases in literature of behavioural finance. It is a psychological bias that arises partly from self-attribution bias. It create belief that investors can predict the market. There is a tendency for investors to regard successes as arising from their expertise while failures are due to bad luck or the actions of others, resulting in excessive confidence in one's own powers of forecasting. To quote Myers (1989:293) on the decision-making process: “Our use of quick and easy heuristics when forming judgements and our bias towards seeking confirmation rather than refutation of our ideas can give rise to the overconfidence phenomenon, an overestimation of the accuracy of our current knowledge”.

In the context of stock market trading, rational investors obtain information in order to increase their level of expected utility. Overconfident investors in this case involve themselves in more trading activity and by doing so they lower their expected utilities, given that the higher the trading level, the lower the expected returns (Odean 1998b). Overconfident investors also tend to hold very risky portfolios than rational investors will do when they are both on the same level of risk aversion (Odean 1998b). This bias is regarded as a good instrument for explaining the irrationality of investors.

Another category of overconfidence bias is the notion of “it won’t happen to me”. This, as asserted by Ricciardi (2008:98), is where: “Individuals consider themselves invulnerable to specific risky activities or events on an individual basis while they would readily concede to these risks on a societal level”. Another bias closely related to overconfidence is the illusion of control. In this case, investors behave as if they are in control of making a good forecast where it is not possible. This is associated with underestimation of risk.

Conservatism

Edwards (1968) identified the phenomenon of conservatism. This explains the reluctance of people to change their opinions when new information is introduced. “Fear of change, and fear of the process of change, can prevent action. This is particularly so if there is uncertainty about costs and benefits of a decision” (4E Journal

2010:9). Conservatism offers an explanation as to why small investors delay investing until the market has risen for a period of time. Small investors often invest just before the market reaches its peak and sell before it troughs (Redhead 2008). Conservatism and anchoring are similar and often difficult to distinguish, for instance, the attitude of people towards changes; in other words anchoring to what they already have and are used to can be defined as conservatism.

2.5.1.4 Emotions and moods

The role of social mood in behavioural finance plays a major part in decision-making. Forgas (1995) submitted that emotions influence decisions on complex and uncertain matters. Redhead (2008) asserts that when people interact socially, they not only receive information and opinions, moods and emotions are also received in the process of interaction. He explains that moods and emotions could affect decision-making even without being related to the decision. Redhead (2008) further distinguishes between moods and emotions, as emotions are related to a particular person, situation or object and occur mostly on a short-term basis, whereas moods have no particular target or stimulus and can persevere for long periods. Moods can be grouped under either positive or negative moods. Positive moods are linked with emotions such as happiness, hope and optimism while negative moods are linked with emotions such as antagonism, fear and pessimism.

Nofsinger (2005) submitted that social mood is reflected in stock markets rapidly and as such the market develops into an indicator of social mood. Nofsinger (2005) referred to the impact of mood on financial decision as the “misattribution bias”. Further biases under emotions and moods are familiarity bias (ambiguity aversion) and decision fatigue, discussed below.

Familiarity bias (ambiguity aversion)

Familiarity bias, alternatively called ambiguity aversion, suggests that investors prefer to invest in companies that they feel they understand. Whittlesea (1993:1235) suggests: “A feeling of familiarity is the ***sine qua non*** of remembering. Judgements about one’s personal past that are not accompanied by a feeling of familiarity do not feel like remembering, but instead feel like guessing or problem-solving. In contrast, a feeling of familiarity is usually sufficient to make one feel one is remembering, whether or not the feeling is accompanied by recall of the detail of a prior experience”. Ricciardi (2008) defined the familiarity bias from a risk perspective as an inclination or prejudice that alters an individual’s perception. This insinuates that people are often more tolerant of what they know with specific circumstances. Risks that are familiar are less feared than unfamiliar risk; this explains people’s reaction to unexpected information.

Also from a behavioural finance point of view, Baker and Nofsinger (2002:101) stated that: “People often prefer things that have some familiarity to them. Consequently, investors tend to put too much faith in familiar stocks. Because those stocks are familiar, investors tend to believe that they are less risky than other companies or even safer than a diversified portfolio”. “Over 90 per cent of the equity investments of investors in the US, UK and Japan is in companies in their own countries. This home bias exists despite the demonstrated benefits of international diversification” (Redhead 2008:29).

Decision fatigue

Behavioural finance explains decision fatigue as a phenomenon whereby "prolonged periods of decision-making deplete investors' mental energy, resulting in poor decision or decision paralysis" (Opiela, CFA Institute Magazine 2012: 35).

Decision fatigue came into limelight when it was documented among a group of judges presiding over parole hearings for Israeli prisoners (Lo 2011, Green 2011 and, Tierney 2011). During each day of hearings, there were two food breaks that divided the day into three sessions. Researchers found evidence of a pattern over these sessions. At the start of the session, it was found that the judges gave favourable parole decisions up to 65% of the time. These parole decisions would systematically decline to nearly 0% by the end of each day. It appears that difficult decisions can be mentally taxing in some manner, so as these sessions wore on, the judges became more inclined to avoid such decisions by denying parole (Lo 2011:34-35).

From the perspective of an investor, it was submitted by Kevin Gardiner (COMPASS 2012:19): "For either fiscal or monetary policy to be effective, investors need to maintain their willpower to stay invested or have the emotional resolve to get invested when long-term buying opportunities present themselves. Unless you have set up investment strategies in periods of calm this can be difficult. You will likely be faced with countless nervous moments where you have to decide what to do with your investments. Each time you face this decision your willpower is eroded slightly and decision fatigue can set in. Fatigued investors have two options: either stop following the markets' response to current events so closely to reduce the potential for further decision fatigue or, get out of the markets to remove the main source of fatigue. The first requires emotional resilience and is the more likely reaction of high-composure investors. The second is more typical of low-composure investors, who are more sensitive to short-term market movements. Either way, the fatigued investor is unlikely to commit more money to risky assets no matter how attractively priced from a longer-term perspective".

In conclusion, we can argue that the 2007-2009 global financial crisis might have left investors fatigued. The long nature of the crisis will mean that investors were trying to make decisions that would be favourable to them. As the crisis extended, investors became exhausted and eventually they stopped making decisions. This fatigue, I speculate, could lead to other cognitive behaviours such as anchoring, conservatism and representativeness, and even loss aversion.

2.5.2 Conclusion and understanding of behavioural biases

Papers in the behavioural finance literature usually use specific bias types to explain specific behavioural shocks. Few, however, attempt to apply the types of potential biases identified by Hirshleifer (2001) as relating to financial crises. And none, to my knowledge, attempt to distinguish between the impact of a single crisis in highly integrated markets and low-integrated markets. This is what I will do in this thesis in Chapter 6 after examining, from an econometrics perspective, whether contagion has occurred in Chapters 4 and 5.

2.6 BEHAVIOURAL BIASES, MARKET STRUCTURE AND FINANCIAL INTEGRATION

I stated in the introduction to this chapter that I believe there is a possible relationship between the strength of financial linkages/integration between markets and the types of behavioural bias that may be observed during contagion events. Although evidence in this respect is quite limited in the literature, a number of papers can be cited that suggest that this may indeed be the case. These are considered in this section.

A number of articles have emphasised channels of contagion such as the asset market, banking and currency channels (Fry-McKibbin, Martin and Tang 2013, Tonzer 2013, Lau and Li 2001) and the two broad causes of contagion: fundamental causes and investor behaviour (Claessens and Forbes 2004, Dornbusch, Park and Claessens 2000). Others have emphasised that contagion is a result of integration and that during crisis integration increases (Collins and Biekpe 2003, Kassim 2013, Cheng and Glascock 2006). The behavioural concept of investor behaviour has also provided views on how the decisions of market participants can lead to contagion effect, in particular herding behaviour (Edwards 2000, Kaminsky, Reinhart and Vegh 2003, Claessens and Forbes 2004). What these literatures fail to buttress extensively are:

1. The identification of behavioural biases that are more prominent in different groups of markets (developed and emerging);
2. Market integration and the role of behavioural biases during a financial crisis.

These two points are very rarely documented and have posed a serious challenge to this thesis. However, because of the low levels of financial integration or high market segmentation between US and African financial markets (Hatemi-J and Morgan 2007, Berger, Pukthuanthong and Yang 2011, Bekaert et al. 2011) as documented above in

Section 2.4.1, I argue that if contagion is found in African markets, it is best attributed to behavioural biases such as herding or information asymmetries during period of uncertainty. Therefore, this thesis will contribute to behavioural literature on African markets. As discussed in Section 2.4, financial crises prompted a surge of literature on integration as a mechanism of crisis transmission (Schmukler 2004, Morales and Andreosso-O'Callaghan 2010, Mendoza and Quadrini 2010, Asongu 2011b, Mulyadi and Anwar 2012, Račickas and Vasiliauskaitė 2012). As integration refers to liberalisation of financial systems, I argue that in the presence of integrated markets such as the US and other developed markets, the channels of contagion are likely to be both the banking system and financial markets (see Pritsker 2001 and Huang 2000 on channels of contagion). My argument to support this is that the 2007-09 crisis had it most prominent manifestation in banking and stock market crashes around the world, particularly in countries that are exposed to the US. In view of the differences in the level of integration between US and African markets and US and other developed markets, this thesis also argues that differences may be reflected in the way in which behavioural factors identified in Section 2.5.1 have an impact on the different group of markets.

One major link identified across the behavioural biases discussed in Section 2.5.1 is that information plays a major role in most types of investors' behaviour. This finds support in Schmukler (2004) who reports: "Financial globalisation leads to a better financial infrastructure, which mitigates information asymmetries and, as a consequence, reduces problems such as adverse selection and moral hazard".

The notion of crowd psychology, herding behaviour, is the most documented bias associated with contagion effect. A study of herding in the market indices of the developed and emerging financial markets of Asia and Latin America found higher levels of herding in emerging markets than in developed markets and higher correlations of herding between two markets belonging to the same region compared with two markets in different regions (Wang 2008). Chen et al. (2005) studied whether emerging market investors are more or less inclined towards behavioural biases and trading mistakes, compared with developed market investors. They took this approach because many studies have documented heuristics in relation to developed markets. The authors found that Chinese investors make trading mistakes, they suffer from the disposition effect and they exhibit representativeness bias. In a comparison of Chinese individual investors and American individual investors, Chen et al. (2007) found that Chinese individual investors are more overconfident than US investors but that individual investors from both countries suffer from a disposition effect and representativeness bias. Chen et al. (2007) assert that people raised in Asian cultures exhibit more behavioural biases than those raised in the US. Khawaja, Bhutto and Naz (2013) studied seven human biases and market development on the Pakistani stock market. The biases investigated include overconfidence, confirmation bias, loss aversion, anchoring, framing bias, status quo and myopic loss. Their results show that most of the biases are significant and have a positive relationship with market development. Only loss aversion provided a negative insignificant relationship with the market. The authors could not conclude that biases have an impact on market development.

A major bias that has been documented in relation to financial integration is the equity home bias. Empirical evidence such as Tesar and Werner’s (1998) has shown that in developed countries (*presumably where integration is higher*) behavioural biases such as the home country bias are decreasing. Coeurdacier and Rey (2011:1) report that despite better financial integration, equity home bias has not reduced much and it was found that: “in 2007, US investors still hold more than 80% percent of domestic equities, which is much higher than the share of US equities in the world market portfolio and the home bias in equities is observed in all developed countries”. Baxter and Jermann (1997) earlier submitted that despite the growing integration of international financial markets, investors do not significantly diversify internationally. Hatemi-J and Morgan (2007), who found no increase in integration despite efforts to liberalise in Nigeria and Zimbabwe, suggest that the home bias hypothesis or informational inefficiency might be the reason for their findings.

Some biases were mainly discussed in terms of their impact in specific country markets without making a comparison between emerging and developed markets. For instance, behavioural biases of disposition effect and overconfidence and their impact on the Estonian stock market was analysed by Čekauskas and Liatukas (2011). Other studies analysed investors’ attitudes in the presence of behavioural biases. For example, Kudryavtsev, Cohen and Hon-Snir (2013) studied the effect of availability heuristic, disposition effect, gambler’s fallacy, herd behaviour and hot-hand fallacy on the magnitude of stock market decision-making and the cross-sectional correlations between the magnitude of these biases for both professional and non-professional investors. Samuelson and Zeckhauser (1988) found that people do not change because of the status quo bias. One major concern about the Ghana Stock Exchange (GSE) submitted by Magnus (2008) is the conservatism bias. Magnus (2008) reported that the GSE has been in existence for nearly two decades but the total number of enlistment companies shows an average of two enlistments per year, which implies that firms still prefer to use the traditional financing institutions, especially the banks, rather than the stock market. Babajide and Adetiloye (2012) found strong evidence that overconfidence, loss aversion, framing, status quo biases and myopic loss aversion exist in the Nigerian security market but their result further shows the negative relationship between the biases and the market. As investors exhibit behavioural bias, the market depreciates in value. Evidence of stock market overreaction is found in South Africa by Page and Way (1992/1993). The authors also reported that investors pay too much attention to dramatic news.

2.7 EMPIRICAL EVIDENCE OF CONTAGION

Section 2.7 gives a detailed description of the different contagion methodologies or testing frameworks that are found in the literature (it should be noted that detailed analysis of the econometric issues is left to later chapters). This is done as part of the process of identifying the gap in the literature that my subsequent research will focus on. This section is divided into two. Section 2.7.1 identifies key papers in detail. These papers reflect on some contagion theories and show the development of contagion methods of estimation over time. Section 2.7.2 provides general evidences of contagion.

2.7.1 Major papers

1. ***King and Wadhwani (1990)***

The first major study that popularised contagion effect was the seminal work of King and Wadhwani (1990). This forms the basis of the contagion model based on correlation coefficients analysis. The study is based on changes in correlations coefficients between markets before and after a shock. If the correlation coefficients increase significantly after a crisis, contagion is said to have occurred. The authors pointed out that it is not surprising for markets in different countries to be correlated and asserted that a standard asset-pricing model allows for such correlation. King and Wadhwani (1990) reported that to interpret data within a framework that assumes all agents are fully informed (Walrasian equilibrium) is inadequate because of the difficulty associated in identifying fundamental links to a crash and the high instability of correlations between markets during a crisis.

King and Wadhwani (1990) tested for contagion in the stock markets of New York (Dow Jones index), London (Financial Times 30 index) and Japan (Nikkei Dow index) during the 1987 US market crash. The purpose of their study was to find out why, during the 1987 crash, all stock markets despite being in different regions and having varied economic circumstances fell at the same time. Their study examined rational expectations and price equilibrium, and modelled contagion as a result of rational attempts to use imperfect information about significant events to equity values. They explained that with rational expectations, relevant information is revealed to agents in market prices as long as the information structure is simple. In such a situation, markets are said to be information-efficient, where prices reflect fundamentals. If, however, the information structure is complex, it will result in a not-fully revealing equilibrium. Consequently, in a not-fully revealing equilibrium, price changes in one market depend on price changes in the markets of other countries by means of structural contagion coefficients. This explains that a market’s mistake or idiosyncratic changes can be transmitted to other markets, thereby causing an increase in volatility. As high volatility is associated with an increase in correlations, it is this feature that provided King and Wadhwani (1990) with the explanation of the uniform decline in equity prices around the world during the 1987 crash.

Their research aimed primarily to explore the possibility of contagion effect as a result of a not-fully revealing equilibrium. To this effect, they paid attention to the problem of identifying Walrasian efficient markets from not-fully revealing rational expectation models. The contagion model covers the period from July 1987 to February 1988. Their research looked at factors such as overlapping and non-overlapping trading hours among the markets, time zone trading and tests for price jumps. They reported that only the effect of New York on London was an observed price jump of an opened market; other price jumps in the model were of shadow prices of closed markets. The assumption of the price jumps test is that when New York opens, the volatility in London should rise. To achieve this, they computed the volatility of half-hourly returns at 15-minute intervals in London using the FTSE 100 index for three sub-periods.

The contagion model is estimated based on hourly data for stock price changes for New York, Tokyo and London covering the period from September to November 1987. They gave priority to the hypothesis that during and immediately after crash, the contagion coefficients increased as volatility was high and then later decreased with a reduction in volatility. The model did not estimate that contagion coefficients are necessarily constant. However, the coefficients are expected to be an increasing function of volatility.

Their result suggests that cross-market correlations increased significantly during the crisis. For London (FT30) and New York (published Dow Jones), which have overlapping trading hours from 13:30 to 16:00 GMT, contagion is supported both before and after crash. Correlation increased from 0.27 between 01/07/1987 and 16/10/1987 to 0.38 between 19/11/1987 and 30/11/1987. Because of circumstances that might have affected the actual prices on both New York and London stock markets around the time of the crash, the correlations for these markets were recalculated using the same period. For the recalculation, the percentage change on the S&P's futures price and the percentage change on the FTSE Futures index were used instead of changes on the Dow Jones and FT30 indices. Again, contagion was supported with even higher correlation, recorded at 0.47. Also, using data on the futures price index for both markets gave a relatively high correlation of 0.75. The high correlation between the indices might be as a result of the market crash, as the correlation fell to nearly the pre-crash level by early 1988; correlation was recorded at 0.194 between 01/12/1987 and 28/02/1988. Similarly, volatility also rose during the crisis then fell back to its pre-crash level in February 1988.

To identify the contagion coefficients between London and New York using time zone trading, a regression model was used. The model estimates the close to open price change in London on the change in the New York price on the previous day from the close of London to the close of New York. Contagion coefficients measuring New York's effect on London increased from 0.21 before the crash to 0.4 after the crash. The coefficient measuring the effect of London on New York increased from 0.18 before the crash to 1.11 during the crash then fell to 0.44 after the crash between 01/12/1987 and 28/02/1988.

With different time zone trading, the contagion coefficient showing the effect of Japan on the US and London and the effect of the US and London on Japan also showed an increase during and immediately after the crash, then returned to its pre-crash level.

It is worth mentioning that this research only focused on advanced markets with no reference to any emerging market. As is rightly stated by the authors, there is the need to extend the research to other markets. Later studies, for example Forbes and Rigobon

(2002), pointed out a number of methodological problems such as heteroscedasticity bias in correlation assessments and proposed an adjustment that led to subsequent development of the correlation coefficient analysis approach.

2. *Forbes and Rigobon (2002)*

Forbes and Rigobon (2002) enhanced the correlation coefficient analysis. Their enhancement has been cited, extended and criticised by several researchers. The majority of papers favour the heteroscedasticity argument raised by Forbes and Rigobon (2002). Their study identified flaws in the simple correlation contagion model that could bias the contagion test. Forbes and Rigobon (2002) argued that testing for contagion based on conditional correlations is subject to a heteroscedasticity bias associated with high frequency data.

Their research focused on three major financial crises: the 1997 Asian crisis, 1994 Mexican devaluation and 1987 US stock market crash. Although Forbes and Rigobon (2002) identified a universal fall in markets during several crises, they found it necessary to define contagion and what it constitutes in the first instance before ascertaining whether or not it was the case in the crises they were investigating. Accordingly, they defined contagion as “a significant increase in cross-market linkages after a shock to one country or group of countries” (Forbes and Rigobon 2002:2223). They were of the opinion that if two markets exhibit a high degree of co-movement during a tranquil period and remain strongly correlated after a shock to one market, contagion may not be the reason for such high correlations. They referred to such a situation as interdependence. According to them, contagion occurs only when co-movements among markets increase significantly after a crash, otherwise an increase in correlations might result from strong linkages that exist among the markets.

Their definition of contagion is restrictive. The reasons for using such a restrictive definition are: (1) it provides a straightforward framework for testing the occurrence of contagion by means of comparing linkages during periods of tranquillity and directly after a shock; (2) it allows for a clearer distinction between alternative explanations on how crises are transmitted across markets.

The test for contagion in Forbes and Rigobon (2002) aimed to prove the inaccuracy and biasness of a simple correlation test for contagion due to its problem of heteroscedasticity. The basis of their argument was that cross-market correlations are conditional on market volatility as such in a crisis period, estimates of correlation coefficients increase and are biased upward. If an adjustment for this bias is not done, a test based on correlation coefficients will usually conclude that contagion occurs. It is worth mentioning that Forbes and Rigobon (2002) credited Ronn (1998) for motivating the discussion on how changes in market volatility bias correlation coefficients.

The origins of crises are identified as the US for the 1987 crash, Mexico in 1994 and Hong Kong in 1997. Their contagion model compares correlations between high volatility and low volatility periods. In this case, the high volatility period is the crisis period, while the full sample is the low volatility period.

The cross-market correlations are estimated using a VAR framework, to adjust for the fact that stock markets open at different times and to control for the serial correlation in stock returns as well as exogenous global shocks. Rolling average two-day returns are calculated based on each country’s aggregate stock market index. The returns are calculated in both US dollars and local currency but focused on US dollars. The intuition behind this is that US dollars are used more often in testing for contagion. To adjust for the serial correlation and variations in trading patterns, they utilised five lags for the transposed vector of returns. Interest rates were also included to control for aggregate shocks and/or monetary policy coordination.

a. *Asian crisis 1997*

Forbes and Rigobon (2002) tested contagion without any adjustment for heteroscedasticity bias from Hong Kong as the country of origin to other markets around the world. The stable period for the 1997 crisis is defined as 1 January 1996 to 16 October 1997, while the unstable period is defined as the period starting 17 October 1997. A one-sided t-test was used to determine if the cross-market correlations were significantly greater during the full period than the crisis period. Their sample markets included East Asian markets, Latin American markets, OECD markets and other emerging markets (India, Russia and South Africa): in total they had 28 countries. Out of 28 markets, 15 markets supported contagion from Hong Kong. Among them, Hong Kong to Indonesia recorded an increase in correlation from 0.38 during the stable period to 0.75 during the turmoil period and 0.428 for the full period. Hong Kong and France had a full period correlation of 0.299 and an increase from 0.227 during the stable period to 0.886 during the turmoil period. Only Mexico recorded the same correlation during the stable period and the full period (0.238).

The adjusted correlation test found no significant increase in correlations from Hong Kong to other parts of the world during the Asian crisis of 1997. The t-test statistics for all the countries failed to support contagion after adjusting for heteroscedasticity, except for Italy, which recorded correlations of 0.191 during the stable period, 0.818 during the turmoil period, and 0.236 for the full period. A test statistic of 1.79 gave evidence of contagion. According to the definition of contagion in Forbes and Rigobon's (2002) research, the high increase in unconditional correlations observed during the turmoil period between Hong Kong and Korea (0.380) and Hong Kong and Germany (0.642) confirmed interdependencies in the markets.

b. *Mexican crisis 1994*

The turmoil period for the Mexican crisis is defined as 19/12/1994, following the devaluation of the peso, to 31/12/1994. The full sample is defined as 01/01/1993 to 31/12/1995.

A test for contagion was carried out without correcting for heteroscedasticity bias, as in the first case of the 1997 Asian crisis. A total of six countries (Korea, Argentina, Brazil, Belgium, the Netherlands and South Africa) showed a significant increase in cross-market correlations, supporting the evidence of contagion. Many of the 28 countries showed an increase in correlation during the turmoil period, although it is not statistically significant. Correlation between Mexico and Russia increased from −0.009 to 0.0077. All the Latin American countries in the sample showed a strong degree of co-movement. However, correlations between Mexico and the Philippines, Spain, Sweden, India and even the US fell during the turmoil period.

After adjusting for heteroscedasticity bias and retesting for contagion, all the unconditional correlations became smaller than the conditional correlation during the turmoil period. For example, the cross-market correlation between Mexico and Australia was 0.092 for the full period, the conditional correlation increased to 0.565 during the turmoil period, but the unconditional correlation increased to only 0.223. The overall result for the Mexican crisis showed no significant increase in cross-market correlation during the turmoil period after adjusting for heteroscedasticity. Various sensitivity tests were employed such as varying the interest rates or adjusting lags and using returns in local currency, which eventually came to a similar result. For the conditional correlation some evidence of contagion was found.

c. *US stock market crash 1987*

For the US market crash of 1987, the turmoil period is defined as 17 October 1987 to 4 December 1987, the stable period covers 1 January 1986 to 17 October 1987 and the full sample period is the stable period and the turmoil period. The sample markets include the US as the origin of the crisis, Australia, Canada, France, Germany, Hong Kong, Japan, the Netherlands, Switzerland and the UK. The same procedure for testing contagion in the case of the Asian and Mexican crises was used.

The first set of results, unadjusted for heteroscedasticity, showed a significant increase in cross-market correlations during the turmoil period in more than half of the countries, with four countries (France, Netherlands, Switzerland and the UK) showing evidence of contagion. After adjusting for heteroscedasticity bias, it was immediately apparent that changes occurred in the correlation coefficients. The unconditional correlation was substantially lower than the conditional correlation during the turmoil period. For instance, the full period cross-market correlation between the US and France was 0.256 but the conditional correlation during the turmoil period increased to 0.610 while the unconditional correlation only increased to 0.441 compared to the unadjusted correlation.

All the financial crises studied by Forbes and Rigobon (2002) [Mexican crisis (1994), East Asian crisis (1997) and the US stock market crash of (1987)] provided no support for evidence of contagion in emerging markets after correcting for heteroscedasticity.

Forbes and Rigobon (2002) acknowledged evidence of a high level of market co-movement during the crises periods, which they termed as interdependence.

3. Collins and Biekpe (2003)

Collins and Biekpe (2003:6) in their study, "Contagion and Interdependence on African Stock Markets" used the narrow definition of contagion as "a significant increase in correlation coefficients over a period of financial turmoil". The purpose of their work was to understand the relationship between African markets and global emerging equity market returns, as well as the relationships between African equity market returns.

The study adopted the Forbes and Rigobon (2002) heteroscedasticity adjustment for correlations to measure contagion from Hong Kong to African markets during the 1997 Asian crisis. The study used daily data on market indices for eight African countries. Rolling two-day averages of daily returns were calculated to allow for differing open market times. The adjusted and unadjusted correlations were only used to investigate contagion from Hong Kong to African markets. The African markets in their sample were Egypt, Kenya, Mauritius, Morocco, Namibia, Nigeria, South Africa and Zimbabwe. The sample period was divided into tranquil and crisis periods. The tranquil period runs from 2 January 1997 to 17 October 1997 while the crisis period is from 20 October 1997 to 28 November 1997. They measured contagion by the significance of increases in correlations during the turmoil period against the tranquil period. This differed from Forbes and Rigobon (2002), who measured contagion between the low volatility periods (full period) against the crisis periods.

Lower weekly frequency data and a longer time frame were used to access the relationship between the African markets. In this case, a simple correlation matrix with unadjusted correlations was utilised. Botswana and Ghana were added to make it 10 African markets in total for this analysis. They explained that the correlation coefficients were not adjusted as the patterns of variances of the African markets differed. A steady increase in variances was observed in some markets over time while in some markets, there were pockets of higher variance. They asserted that the changes in correlations were due to the changes in variances observed through time.

The unadjusted contagion test provided evidence of contagion in Egypt, Mauritius, South Africa and Namibia, while the remaining countries found no contagion. After adjusting for heteroscedasticity, the contagion effect found in Mauritius and Namibia disappeared but South Africa (2.100 test statistic) and Egypt (3.022 test statistic) remained significant. Collins and Biekpe (2003:10) provided this viewpoint: "Intuitively, South Africa is a significant player in the emerging market arena, in terms of market capitalisation, value traded and its weight in the International Finance Corporation Investibles (IFCI) index, and therefore would be more heavily influenced by international investors. Within an African context, Egypt is the next largest market included in the IFCI index. It stands to reason that those countries would be more likely to experience contagion, perhaps via herd behaviour or a portfolio rebalancing by an international investor base, than the smaller markets in Africa".

Regarding the relationship between African markets, the researchers found that the strongest relationships were within the Southern Africa region: between South Africa and Botswana, Namibia and South Africa, and Botswana and Namibia. Again South Africa demonstrated a strong interregional relationship.

Their result was inconsistent with Forbes and Rigobon (2002), who found no contagion in South Africa during the Asian crisis in 1997. This difference in result they attributed to the slight difference in the estimation of their t-test statistics from that of Forbes and Rigobon (2002) and the sample period used. Forbes and Rigobon (2002) used a tranquil period starting at the beginning of 1996 while Collins and Biekpe (2003) used a tranquil period starting at the beginning of 1997.

The researchers concluded that the evidence of contagion found in Egypt and South Africa could be that African equity markets offer diversification for global emerging market managers. As for the relationship between African markets, the researchers reported that: "This would be explained by fundamental trade and economic links, such as the strong relationships within Southern Africa, rather than investor behaviour links. The only relationship that appears not to be linked by fundamental influences are those that show evidence of contagion to global financial events, Egypt and South Africa. The explanation may lie in the role international investors have come to play in both markets". (Collins and Biekpe 2003:13)

4. *Arestis et al. (2005)*

Arestis et al. (2005), enhanced the conditional correlation analysis by detecting structural breaks on the full sample. The authors tested for contagion as a positive shift in correlation between asset returns from the four largest emerging markets of Asia, namely Thailand, Indonesia, Korea and Malaysia, to a set of developed markets, namely Japan, the UK, Germany and France (major lenders) during the 1997 East Asian crisis.

In their research, they defined contagion as a significant increase in cross-market linkages after a shock to one market. Although they employed other tests, they also adopted the corrections by Forbes and Rigobon (2002) and Rigobon (2004) for biases resulting from heteroscedasticity, endogeneity and omitted variables. The main focus of this research was the exposure of the major international lenders to contagion from the four largest emerging economies.

The contagion model estimated in their research was based on the conditional correlation analysis between assets returns. This research differs from earlier work in the field of contagion by the estimation of a full sample period instead of dividing the period into crisis and non-crisis periods or low volatility and high volatility periods, as seen in King and Wadhwani (1990) and Forbes and Rigobon (2002). They also selected breakpoints that matched the beginning and end of the contagion period through a series of dummy tests and computed the critical values of the test by means of a bootstrap.

Arestis et al. (2005) indicated that Caporale, Cipollini and Spagnolo (2005) introduced the sequential dummy test they employed in determining the endogenous breakpoints that denote the period of contagion. They asserted that the test relied on a more plausible identifying restrictions compared with earlier work.

To test the evidence of contagion, the Wald test was used. Their research used weekly stock data from the eight markets under study, covering the period from the first week of August 1990 to the last week of July 1998. They chose the end date of July to avoid an overlap with the Russian crisis, which started in August 1998. As mentioned earlier, breakpoints that denoted the period of contagion were selected. To achieve this, the researchers considered various specifications for the step dummy, such as allowing for the start date of contagion ranging from January 1997 to June 1998. The period that had the largest Wald statistic was then selected. If the Wald statistic is significant, as well as the coefficients associated with the step dummy being positive and significant, contagion is said to have occurred.

They found evidence of contagion between the major lenders to the emerging markets, which they attributed to the reduction in bank lending from the major international lenders. For instance, developed countries reduced their exposure to the emerging markets between 1997 and 1998. Lending from Germany to Korea fell from US$10,968 billion in 1997 to US$8,678 billion in 1998, while France to Korea fell from US$11,349 billion to US$8,440 billion in 1998. In a similar fashion, other developed countries in the sample also reduced their lending to emerging markets over the years. The contagion test specifically revealed that even though lending from France to Malaysia fell from US$2,885 billion in 1997 to US$2,391 billion in 1998, Malaysia provided no contagion with France but provided support for contagion with Germany, Japan and the UK. Contagion was also evident between South Korea and France, and South Korea and Japan, but absent between South Korea and Germany, and South Korea and the UK. Thailand and Germany gave no evidence of contagion but, evidence of contagion is found from Thailand to the three remaining major lenders.

Strikingly, they found that Japan was the only country that had a contagious effect with each of the emerging markets under study. Arestis et al. (2005) reported that there was contagion from Indonesia to the UK and from Korea and Thailand to France. They indicated that the UK was largely exposed to Indonesia while the largest exposure from an international lender country to emerging economies was from France to Korea and Thailand.

In conclusion, Arestis et al. (2005) reported that the impact of the East Asian crisis on developed financial markets was minimal because of the diversification of risk through the reallocation of bank loans, drastic reduction of exposure on the part of Western and Japanese banks to emerging markets and prudential supervision and regulatory policies.

The reduction in exposure of the major international lenders had a serious contagious effect to the East Asian economies. The findings of this research were inconsistent with those of Forbes and Rigobon (2002) because the authors reported evidence of contagion during the Asian crisis. This study however, failed to extend the research to any African market.

5. *Wang and Thi (2006)*

Using DCC-bivariate GARCH, Wang and Thi (2006) investigated the existence of contagion effects between the stock markets of Thailand and the Chinese Economic Area (CEA). The sample included the indices of China (Shang Hai B-shares), Hong Kong (Hang Sheng index), Thailand (Bangkok index), and Taiwan (Taiwan Weighted) over the period 21 February 1992 to 15 November 2000. The contagion test of Wang and Thi (2006) was carried out in three stages;

First, they detected structural breaks by employing the iterated cumulative sum of squares (ICSS) proposed by Inclán and Tiao (1994). This was to determine if the samples included financial crisis and also because it had been raised earlier by Lamoureux and Lastrapes (1990) that ignoring structural breaks could lead to the overestimation of heteroscedasticity and affect the reliability of applications. Also, in the opinion of Hansen (2001), structural breaks are endogenous and determined by the data, which could lead to the model being set up wrongly.

The second step was the application of the DCC-bivariate GARCH of Engle (2002) to estimate the correlation coefficients between stock returns in accordance with the pre-crisis and crisis periods, as identified by the ICSS in step one. An estimation of Engle's (2002) DCC model itself requires two stages: a) the first stage is to estimate the univariate GARCH model, and b) the second stage is to estimate the correlation coefficient. It was reported that GARCH (1, 1) captures the characteristics of heteroscedasticity of stock and financial variables (Bollerslev, Chou and Kroner 1992, Morales and Andreosso-O'Callaghan 2010). Wang and Thi (2006:24) provided this viewpoint: "The correlation coefficients between stocks returns estimated by the DCC-bivariate GARCH model, in the progress of time, varies with market variances. Therefore, the conventional contagion effect test that ignores the adjustment of heteroscedasticity can be improved".

In the third step, the t-test was used to check the existence of contagion, based on the means of the correlation coefficients of the pre-crisis and crisis periods identified by the ICSS estimated through the DCC model.

Their finding suggested positive conditional correlation coefficients and an increase in co-movement among the Thai and CEA markets. They explained that the Asian meltdown, which began in Thailand, transmitted to other countries in the region through various channels, of which the stock market was a very important one. "Consequently, rapid economic integration within the CEA, consisting of China, Hong Kong and Taiwan, has caused these markets to be badly hurt by the crisis. However, the economic integration is stronger and needed for the globalisation process. Therefore, we must learn how to live with contagion". (Wang and Thi 2006:34)

The research concluded that evidence of contagion effects were found during the Asian crisis in the region. This occurred during a period of exceptional economic growth. This meant that investors needed to pay close attention to what was happening in neighbouring markets and that financial exogenous shock, would increase if economic, financial and market information was ignored.

6. Khalid and Rajaguru (2006)

On the Asian crises, Khalid and Rajaguru (2006) used daily data on the exchange rate of each country's domestic currency against the US dollar to study the interlinkages between currency markets among ten Asian countries (India, Indonesia, Japan, South Korea, Malaysia, Pakistan, the Philippines, Singapore, Taiwan and Thailand) covering the period 5 January 1994 to 31 December 1999.

The sample period was divided into four (full period, pre-crisis period, crisis period and post-crisis period) in order to find out whether contagion was supported strongly during the crisis period. The full period was from 1994 to 1999, the pre-crisis period covered 5 January 1994 to 1 July 1997, the crisis period span from 2 July 1997 to 30 June 1998 and the post-crisis period was from 1 July 1998 to 31 December 1999.

The countries were divided into crisis-hit Asia and non-crisis-hit Asia. They constructed a multivariate GARCH model and applied Granger causality to identify the interlinkages among exchange rate markets in the Asian countries. They found strong evidence of inter-market linkages within the Asian currency markets in the full sample and during the crisis and post-crisis periods. The pre-crisis period did not provide very strong evidence. The results from the Granger causality tests provided weak support for contagion. Their results indicated an increase in currency market links during and after the crisis.

They also reported that the Indian rupee had become more vulnerable to regional currency markets following India's recent development of investment zones to attract foreign investment and its receipt of substantial foreign direct investment (FDI). Also, they found no strong currency linkages within non-crisis-hit Asia, but the non-crisis-hit Asian countries were linked to currency markets in the crisis-hit Asian countries.

Their results supported evidence of contagion by means of a common creditor – in this case Japan. They explained that a shock in the crisis-hit East Asian market that changed the Japanese yen could be transmitted to a non-crisis-hit Asian country such as Pakistan, because of Japan's position as a common creditor. This finding was in line with Kaminsky and Reinhart (1999), who investigated the role of a common-banker-lender channel as a main determinant of international propagation of shocks; they found that this channel played a major role in emerging countries.

7. *Beirne et al. (2009)*

Beirne et al. (2009) estimated the tri-variate GARCH-BEKK models of returns in mature, regional emerging and local emerging markets. The research was aimed at examining volatility spill-over from mature to emerging stock markets; tests for changes in the transmission mechanism for contagion when mature markets are in crisis and; the implications for conditional correlations between mature and emerging market returns. They adopted Forbes and Rigobon's (2002) concept of shift contagion and defined volatility contagion as the shift in volatility transmission from mature to emerging markets during turbulence in the mature markets.

A dummy variable was included in the model to capture the parameter shifts during turbulence. The sample markets consisted of 41 emerging market economies from Asia, emerging Europe and South Africa, Latin America, and the Middle East and North Africa (MENA). Weekly stock returns were used. The time frame for the Asian crisis ran from September 1993 to March 2008 while that of emerging Europe and South Africa, Latin America and MENA started from 1996 and also ended in March 1998.

The authors also carried out likelihood ratio tests to examine a number of hypotheses regarding the transmission of volatility from mature to regional and local emerging markets and also from regional to local markets. The likelihood ratio tests suggested that conditional variances in many of the emerging markets were influenced by mature markets as the spill-over parameter changed during the turbulent period. However, they reported limited evidence of shifts in conditional correlations between mature and emerging markets although the conditional variances of most of the emerging market economies increased during the crisis episodes studied. They concluded that the increase in conditional correlations was very much limited to emerging Europe.

8. *Lee, Wu and Wang (2007) and Asongu (2011a)*

Every now and then irregular events take place in different parts of the world, such as the London Tube bombings, the 9/11 attack on the US and natural disasters around the globe. These events are not expected and are therefore not planned for. When they occur, the financial market of the affected country usually suffers heavy damage, which may spill over to other countries. Contagion research has been extended to investigate some of these irregularities.

In one research on these kinds of events, Lee, Wu and Wang (2007) investigated whether contagion had occurred across 26 international stock indices and exchange rates after the South East Asian earthquake of 26 December 2004. The sample size covered 26 December 2003 to 25 March 2005, divided into the non-crisis period (26 December 2003 to 25 December 2004) and the crisis period (26 December 2004 to 25 March 2005). The Indonesian equity and foreign exchange markets were the base criteria. The study employed the correlation coefficient method. They found no evidence of contagion effect in any of the stock markets but some evidence in the foreign exchange market after the 2004 South East Asian tsunami. The researchers concluded that the earthquake primarily affected countries in the Asian region because of the tsunami in East Asia; they referred to the contagion effect as geographical.

Another recent work that studied an irregular event was Asongu (2011a). Asongu's study focused on the Kenyan crisis and risk of contagion effect to other markets from 27/12/2007 to 28/02/2008. Asongu investigated eight African markets (Botswana, Egypt, Mauritius, Morocco, Namibia, Nigeria, South Africa and Tunisia). In addition, Lebanon was also part of the sample countries. Asongu (2011a) adopted the Forbes and Rigobon (2002) approach in the context of Collins and Biekpe (2003). The sample period was divided into a two-month pre-crisis (stable) period and a one-month crisis (turmoil) period. The stable period covered 01/11/2007 to 24/12/2007 and the crisis period was from 04/01/2008 to 29/01/2008. This viewpoint is provided in the research: "We assume here that any substantial price sensitive political implication should have occurred after the announcement of the election results (30/12/2007). More so, the full crisis period (27/12/2007 to 28/02/2008) is not assumed as the turmoil period because a stock market shock was not experienced during the entire period". (Asongu 2011a:6)

Asongu's (2011a) study found that Lebanon, Mauritius and Nigeria were contaminated. The author concluded that political instability in Africa does not have isolated within-country financial effects. The findings support the hypothesis of growing integration of African stock markets.

9. *Malik and Ewing (2009)*

Using the bivariate GARCH model, Malik and Ewing (2009) studied the volatility transmission between oil prices and five different US sector indices (financial, industrials, consumer services, healthcare and technology). The research used weekly returns, which were calculated from daily data over the period 1 January 1992 to 30 April 2008.

The study showed that the volatility of oil returns was significantly affected by its own news and past volatility, and that news from the financial sector indirectly affected the volatility of oil return. As such, a positive shock in the financial market was associated with a decline in the volatility of oil returns. Also, volatility of returns from the financial sector was affected by its own news and volatility. No direct or indirect evidence on the impact of oil return volatility was found. These findings indicated that financial market stability measured by conditional variance of returns would not be affected by oil market shocks. As for the technology sector, the results gave evidence that the volatility of technology returns was directly affected by its news and volatility and indirectly affected by shocks and volatility in oil returns. Thus changes in oil returns would increase volatility in the technology sector. In terms of the consumer sector, it was found that the volatility of oil returns was affected by its news and volatility and also by the return volatility from the consumer sector. On the other hand, the consumer return volatility was affected by volatility in the oil sector. Healthcare returns volatility was found to be directly and indirectly affected by volatility in oil returns, while the volatility from the oil returns was indirectly affected by the healthcare sector and affected directly by its news and volatility. The indirect impact from the healthcare to the oil sector was compatible with the fact that healthcare has been relatively steady over time. Finally, for the industrial sector, they found oil returns volatility to be indirectly affected by the volatility of returns from the industrial sector and affected directly by its news and volatility. However, the volatility of returns in the industrial sector was only affected by its news and volatility. This indicated that the industrial sector was not affected by shocks and volatility from the oil sector.

The general conclusion from the research was that significant interaction between the volatility of returns especially in the oil and equity markets was attributed to cross-market hedging and sharing of common information by investors. This means that investors should keep a close watch on different markets because news in one sector may have an impact on other markets through various interdependencies.

10. Morales and Andreosso-O'Callaghan (2010)

A new empirical advancement to contagion literature is the work of Morales and Andreosso-O'Callaghan (2010). It first adopted the Forbes and Rigobon (2002) approach. In line with Billio and Pelizzon's (2003) argument on the Forbes and Rigobon (2002) approach (that it is highly affected by the size of the windows used and omitted variables); the authors proposed a second approach that entailed testing for contagion using the residuals from GARCH (1, 1).

Morales and Andreosso-O'Callaghan's (2010) research was inspired by the recent financial crisis (2007-2009), which started in the US and made the debate on contagion more popular than ever. The researchers found it necessary to study and analyse the crisis before concluding the existence of contagion. They explained that although the US is interconnected with many economies around the globe, what appears to be contagion might just be spill-over effect arising from interlinkages across markets. The researchers argued that if it were contagion, it would take the world a long time to recover, but at the time of their research some countries were beginning to recover. They also pointed out that other countries did not present the same problems that were affecting the US economy; therefore, the conclusion that the financial crisis was contagious had to be drawn with care.

The research studied the recent financial crisis from a world market perspective and also from a regional perspective. A total of 58 world economies were analysed, which were grouped regionally: America, Europe, Asia and Africa. The stock markets were further divided into six sub-regions as African markets, American markets, Asian markets, Eastern European markets, European markets and Middle East markets. The intuition behind grouping the countries was to identify *behavioural patterns* among the regions.

The research covered the period January 2003 to May 2009, using daily adjusted stock price data for all the countries under analysis. The sample was divided into crisis and non-crisis periods and the US was identified as the origin of crisis. The turmoil period was identified as the period covering October 2007 to May 2009 while the period of tranquillity covered January 2003 to September 2007. The definition of contagion given by Forbes and Rigobon (2002) was adopted in this research. Three different models were used to conduct the contagion analysis:

The research first adopted the Forbes and Rigobon (2002) model based on correlation where asset returns are first scaled before testing for contagion in a regression framework.

The second procedure adopted by the researchers was motivated by Billio and Pelizzon (2003), who criticised Forbes and Rigobon's (2002) contagion model as being affected by the size of the windows. Morales and Andreosso-O'Callaghan proposed using the GARCH (1, 1) model to counter problems of omitted variables. Dummy variables for the pre-crisis and crisis periods were also included in the model. Considering that the GARCH (1, 1) gives a good description on financial asset returns, Morales and Andreosso-O'Callaghan (2010) concluded that the AR (1)-GARCH (1, 1) was most appropriate to test for contagion.

The last model extended the second model by incorporating GARCH errors per regional market to adjust for shocks originating in the regional market. This was to check whether market volatility was greatly affected by shocks from the regions rather than the initial event in the US stock markets.

Using the two American indices (Dow Jones and S&P500) to test for contagion to the African markets (Egypt, Kenya, Morocco, Nigeria and South Africa) within the three models provided an interesting result for the authors. Egypt was the only African market that had a significant p-value indicating the presence of contagion within all frameworks. Kenya was also significant with both indices but only within the first model. Nigeria had no contagion with either of the indices within all three frameworks. South Africa and Morocco had contagion with only S&P500 within the first model.

The Asian markets in the study comprised of Australia, Shanghai, Shenzhen, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Pakistan, the Philippines, Singapore, Taiwan and Thailand. With the exception of Australia, Hong Kong, India, the Philippines and Thailand, the rest of the markets in this group showed evidence of contagion from Dow Jones within the first model. As regards to S&P500 within the first model, no contagion was found in Australia, Hong Kong and Japan. Contagion was only present in Thailand and India for the S&P500 within all three frameworks. More surprising to the authors is the absence of contagion in all facets from Australia and Hong Kong, especially that of Hong Kong considering the catastrophic Asian financial crisis of the late 1990s.

Within the Middle Eastern region, which comprised Israel, Jordan, Oman and Qatar, only Israel showed the presence of contagion within all models from the two US indices, while the rest of the markets detected no contagion in all aspects.

The fourth sub-region was the American markets, which included Canada, Argentina, Brazil, Chile, Columbia, Mexico, Peru and Venezuela. No contagion was detected in Venezuela for both indices within the three models. Argentina, Chile and Columbia had the same result of no contagion with both indices within the first model, but had contagion with both indices within the second and third model. Mexico was the only market exhibiting contagion effect from S&P500 within the three models, while from Dow Jones contagion was detected in the second and third model but not in the first model. It is also worth mentioning that contagion was found in all countries with Dow Jones except Venezuela within the second model.

In the Eastern European sub-region made up of nine markets (Croatia, Czech Republic, Hungary, Poland, Romania, Russia, Slovenia, Turkey and Ukraine), there was consistency from both indices within the first and third models. The results showed that there was contagion in Croatia, Hungary and Romania within all models with both indices.

The largest sub-region comprised of the European stock markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Spain, Sweden, Switzerland and the UK. The general finding in this group was the lack of contagion, with an exception in the case of Ireland, which provided evidence of contagion in all three models with both indices. The UK, Italy and Iceland, on the other hand, provided not a single case of contagion with both indices.

2.7.2 Further empirical evidence on contagion and cross-market transmission of crisis: alternative methodological approaches

Masih and Masih (1997) tested the relationship among six stock markets of developed nations, the Dow Jones (US), Nikkei (Japan), CAC (France), Canada, DAX (Germany) and FTSE (UK), before and after the stock market crash of 1987. They used the co-integration technique on end-month closing share price indices. They found that despite the crash, Dow Jones which was the leading market still remained top among the sampled markets while the FTSE and DAX indices showed more dependency on their indices. They concluded that the crash brought about a greater interaction among markets, but they did not explicitly test for contagion. However, they found a single co-integration vector over each of the pre-crash and post-crash samples.

Baig and Goldfajn (1999) used daily data from 1995 to 1998 from a set of Asian countries (Thailand, Malaysia, Philippines, Indonesia and Korea) to test for contagion during the Asian crisis of the 1990s. They studied the correlations between countries of their respective equity, foreign exchange, interest rate and sovereign debt markets. They then applied a VAR methodology to estimate the impulse responses to shocks in each of the currency and stock markets. Finally, they tested whether the correlations had significantly increased after the crisis compared to the tranquil period correlations. In the event that they found there to be no significant increase in correlations after the shock, then they would attribute the pressure felt by the market to some common cause or spill-over effects. They found a significant increase in correlation in the currency and sovereign spreads indicating contagion, but the equity market correlations provided mixed evidence**.** The authors explained that the Asian crises suggested that market participants moved together across a range of countries during financial instability as such a shock from one market is readily transmitted to other markets causing substantial instability.

To investigate contagion across six developed and emerging Asian markets and also the US during the time of the Asian currency crisis of 1997, Thanyalakpark and Filson (2001) extended the GARCH model by using a stationary multivariate asymmetric GARCH specification of international capital assets pricing model. The developed markets included in their samples were Hong Kong, Japan and the US, while the emerging markets were Korea, Thailand and Malaysia. They referred to contagion as ***herd behaviour*** resulting from investors pulling out of a market because of a change in their expectations as a result of a shock in another market. Their theory was that if herd behaviour was a factor in the crisis, correlations between the affected stock markets should rise even after controlling for the important aspects of own-country risk. The approach they took to investigate if herd behaviour was a factor was to test whether correlations between stock markets returns increased after the crisis started. They reported contagion effect only from Thailand to Korea, while other markets showed interdependence.

Mathur et al. (2002) investigated contagion effects in the Chilean market and the Chilean American Depository Receipts (ADRs) trading in the US from the 1994 Mexican peso crisis using four approaches: event study, regression analysis, multifactor regression model and variance decompositions. Their results supported contagion. For the event study test, they found that the Chilean stock market reacted negatively to the devaluation news of the Mexican peso. The result from the multiple regressions suggested that during the event, changes in the Chilean peso IGPA index affected the pricing of the ADRs and that spill-over contagion effects from the Mexican market were transmitted through the Chilean market to the Chilean ADRSs. The multifactor regressions found that during the peso crisis, the Chilean peso returns on IGPA were the determinants of returns on the Chilean ADR portfolio and that the Chilean index expressed in local currency had more significant influence on the pricing of the Chilean ADRs than when expressed in US dollars. Finally, the variance decomposition results indicated that returns on the Chilean index were influenced by returns on the Mexican index, US index and the ADR portfolio. The Chilean index explained nearly half of the variance in the ADR portfolio returns and that exchange rate innovations had no significant contribution to the pricing of the Chilean ADRs. The results from their findings indicated that during the crisis, investors did not pay attention to exchange rate-based asset pricing. As such, they priced the Chilean ADRs with regard to the Chilean index without considering changes in the exchange rate in the market. Instead, they applied the home country Chilean index unadjusted for exchange-rate fluctuations to price Chilean ADRs denominated in US dollars.

Moussalli (2007) analysed the extent to which the Asian currency crisis affected 32 nations. The sample countries were divided into three regions: Asia (China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan, Thailand and Vietnam), Latin America (Argentina, Brazil, Bolivia, Chile, Columbia, Mexico, Paraguay, Peru, Uruguay and Venezuela) and Eastern Europe (Russia, Hungary, Poland, the Czech Republic, Estonia, Latvia, Lithuania, Ukraine, Romania and Slovenia). In order to measure the severity of the crisis the study employed a cross-country regression analysis to test the relationship between the dependant variables and the independent variables. The dependant variables were depreciation and stock prices, while capital controls, law and order, corruption and fixed exchange rate were among the independent variables. The regression framework also included dummy variables. Moussalli (2007) found that countries with weak institutions were associated with a more severe crisis, as were countries with more capital controls and weak institutions, while countries with flexible exchange rates, weak institutions and low capital controls were less associated with the severity of the crisis. The study concluded that weak institutions, high capital controls and fixed exchange rate combined increased the panic effect, which in turn led to contagion and the severity of financial crises. More importantly, Moussalli (2007) found that belonging to a region was a better explanation for the severity of the crisis than any of the macroeconomic variables in the study.

Essaadi, Jouini, Khallouli (2009) investigated contagion in seven East Asian markets during the Asian financial crisis, which began in July 1997. The research adopted the Forbes and Rigobon (2002) and Rigobon (2003) terminology of shift contagion as the increase in cross-market interdependencies estimated with correlation among assets' returns during crisis. They found that after the devaluation of the Thai baht on 2 July 1997, structural changes occurred in the links among the markets. An increase in correlation between Thailand and each of the other Asian markets was recorded in a pair-wise relationship. They also demonstrated the existence of shift contagion in the East Asian region as a result of the Thai baht devaluation, which led to a surge in the market. They concluded that the increase in interdependencies is linked with a structural break that shows the generation of new transmission mechanisms among countries that does not exist during the period of tranquillity. The identified new transmission mechanisms reflected changes in investors' expectations.

2.8 CONCLUSIONS: IDENTIFYING GAPS IN THE LITERATURE, IDENTIFYING THE RESEARCH QUESTION AND IDENTIFYING NOVELTY IN THE THESIS

From an African perspective, the 2007-09 crisis was unique as it was the first time that a major financial crisis in another part of the world represented a potential contagion event on the continent. This possibly was a reflection of increasing globalisation and increases in the integration of Africa's expanding financial markets with the rest of the world. Previous contagion events cited in the literature affected countries with similar features (for example, the Asian financial crisis). The 2007-09 crisis, however, appeared unique as it was truly global.

From a literature perspective it can be argued that there are a considerable number of gaps in our current body of knowledge. These range from methodological issues in terms of how we should measure contagion from an econometric perspective (see Section 2.7 and discussed in detail in subsequent chapters) to explaining the process by which a contagion event unfolds. For example, from the literature it can be identified that there are a number of possible channels that a contagion event can follow (see Section 2.3). The chapter also cites some evidence from the literature that suggests that the strength of financial linkages/integration will influence how contagion will manifest itself. From my analysis the following research gaps are identified.

1. ***Methodology: to identify which of the constant correlation and the dynamic conditional correlations methodologies are most appropriate for the examination of contagion effects in Africa and selected other international markets.***

- A number of studies focused on adopting, extending or developing further the work of Forbes and Rigobon (2002) in the light of criticism of their original methodology. A number of researchers adopt more than one methodological approach in their studies on robustness grounds (for example, Mathur et al. 2002, Morales and Andreosso-O'Callaghan 2010, Bekaert, Harvey and Ng 2005). An important caveat is that the econometric approaches employed in investigating contagion can reflect differences in the definition of contagion (for example, Collins and Biekpe 2003, Forbes 2012).
- This thesis will make a novel contribution to the literature by making adjustments to the statistical framework in the light of criticism of the Forbes and Rigobon (2002) methodology. These include (i) *using separate VAR systems to compare the crisis period against the pre-crisis period and (ii) applying a* DCC-GARCH approach (Engle 2002).

2. ***The application of contagion testing to a cross-section of both emerging and frontier African markets.***

- Current contagion studies cited in the literature focused on emerging markets in Asia and Latin America. From an African perspective, studies focus on a single larger African emerging market (mainly South Africa: see Forbes and Rigobon 2002, Arestis et al. 2005). Morales and Andreosso-O'Callaghan (2010), Asongu (2011a and 2011b) and Collins and Biekpe (2003) do consider a number of African countries but no studies examine the broad cross-section of emerging and frontier markets I consider in my thesis. In doing this I will make a novel contribution to the literature.
- The level of correlations found before the crisis will identify which African market is the most integrated with the US. In addition, all markets studied will

either be classed as a highly integrated market or a low-integrated market. If this distinction holds true, this thesis submits that it will be possible to characterise different forms of contagion in respect to the value of correlations before and during crisis.

3. ***Identifying the channels through which contagion events develop within the context of appropriate theory (behavioural and/or non-behavioural models).***

- Existing literature can be cited that describe contagion events in terms of herding. However, none, to my knowledge, attempts to use a number of behavioural bias-related concepts to describe the process by which a contagion event develops across different regions of the global financial market. Economic literature identifies many cases of theories being adapted by synthesis to reflect new economic environments. For example, the Phillips curve was adjusted by Friedman to produce the expectations-augmented Phillips curve. Another example is the synthesis of Keynesian economics with classical economics to produce neoclassical economics. In respect to the contagion literature, I believe that a similar synthesis of academic ideas can be made through the application of behavioural finance to explain the contagion process. In doing this I believe that I am making a novel contribution to the literature.
- The research will attempt to provide behavioural explanations to econometric analysis of data. It will go beyond ascertaining that unexplained high correlations results from investors' behaviour or herding. It will attempt to identify likely biases resulting from heuristic simplification, social effect, self-deception or emotions and mood that might have played a part during the crisis. I found support for this approach in the work of Hovde (2014:73), who states

that: “Behavioural finance is gaining wider acceptance in the financial planning field, especially in light of the recent credit crisis. Everything cannot be quantified and reduced to formulas and numbers-the markets are created and used by humans, who are not perfect. We all have various emotions, and we do not always behave rationally. Our behaviour as investors, whether rational or not, has an impact on the market”.

4. ***Identifying how differences in the extent of market integration influence the ways that contagion events unfold in developed markets and emerging/frontier African markets***.

- Many authors argue that the degree of financial market linkage/integration determines how vulnerable countries are to financial crisis (Collins and Biekpe 2003, Schmukler 2004, Sinha and Pachori 2014). While others submit that most African markets except South Africa are largely segmented from world market (Hatemi-J and Morgan 2007, Bekaert et al. 2011, Berger, Pukthuanthong and Yang 2011), African markets have a variety of institutional features that differentiate them from developed country markets and other emerging markets. As such, it is useful to examine the effect of the crisis on developed markets to provide a means of comparison between developed and African markets. Other high-growth emerging markets (China and India) are also included in the sample for comparative purposes. Assessment of correlations of the markets will answer how differently the crisis affected the markets. In this thesis I will make a novel contribution by examining whether different behavioural factors (biases) can account for differences in the ways in which contagion events develop between developed and emerging/frontier African markets.

3 DATA DESCRIPTION, HYPOTHESES DEVELOPMENT AND METHODOLOGICAL NOTES

3.1 INTRODUCTION

This chapter starts by providing information on the data used and sources of the data. The research periods are identified in Sections 3.2.1.1 and 3.2.1.2. The primary case study of the thesis examines the relationships between the US and African stock markets and covers the period January 2007 to October 2009. There are a total of 10 African countries. The relationship between US and developed markets is also explored to provide a basis for differentiating between the impact of the crisis on emerging/frontier markets and developed markets. For further comparative purposes, additional non-African emerging markets from Asia are incorporated into the analysis.

This chapter then discusses (and justifies) the developed hypotheses of the thesis in Section 3.3. The section also produces a preliminary model of how the financial crisis develops. This model will be tested in subsequent chapters. It also identifies expectations in respect to results.

Section 3.4 identifies the two main methodologies I use for testing contagion effect. These are firstly, *Constant Correlation Coefficient Analysis* and secondly, *Dynamic Conditional Coefficient Analysis* (using multivariate GARCH).

3.2 DATA DESCRIPTION

3.2.1 Identifying the crisis period

Identifying a starting point as well as an end point of a crisis is not clear cut and is subject to argument. The crisis developed slowly at first. Its genesis was in the US sub-prime mortgage market and was associated with high default rates among mortgagees. Although commentators such as Nouriel Roubini warned about the impending crisis in 2006[6] it was not until 2007 that stock prices in the US started to fall significantly and major casualties were observed. For example, on 17 July 2007, Bear Stearns (an investment bank) announced that investors would get little or no money from their investments in its two hedge funds, which were on the verge of collapsing. Subsequently, other big institutions around the globe such as PNB PARIBAS and Northern Rock also announced they had problems and might need help.

Most of the contagion studies found in the literature have not faced major issues in identifying the contagion event as these events have been relatively short-lived (see, for example, Table 3.4 below). The 2007-09 crisis was unique among post-1945 financial shocks in that it developed over a relatively long period. This makes identifying the event window potentially problematical. However, since the crisis originated from the US we have the VIX at our disposal to identify which events in the crisis produced the greatest "shock" to investors. I use this as my tool to identify contagion events in my analysis. The index is popularly known as the "fear index" or "fear gauge"[7] given that it has forward-looking properties. It measures the S&P 500 index options and it reflects market volatility expectations over the next 30 days. The index has been incorporated

---

[6] See, for example: http://www.economicpredictions.org/who-predicted-the-financial-crisis.htm. Access date: 6/06/2014

[7] See, for example, the popular investor web-site: http://www.marketoracle.co.uk/Article42579.html. Access date: 6/06/2014.

into other credible research (See Becker, Clements and McClelland 2009, Ciarlone and Piselli 2009, and Duan and Yeh 2008).

3.2.1.1 Long crisis period (15/09/2008 – 15/10/2009)

The index covering the period 2006-2012 is presented in Figure 3.1 below. It can be noted that the index showed a marginal upward trend between the start of 2006 and the third quarter of 2008 as the crisis began to develop. The sudden increase in the last quarter of 2008 can be identified as being associated with the lead up to the Lehman bankruptcy (15 September) and similar events surrounding it, such as the Federal takeover of Fannie Mae and Freddie Mac (7 September), the emergency US$85 billion loan to insurer AIG (17 September) and the crisis-induced sale of Merrill Lynch to Bank of America (14 September). The Lehman bankruptcy was the defining event of this period and was associated with a sharp spike in the VIX (see Figure 3.1). I therefore use 15 September 2008 to identify the start of what I define as the *long crisis period*.

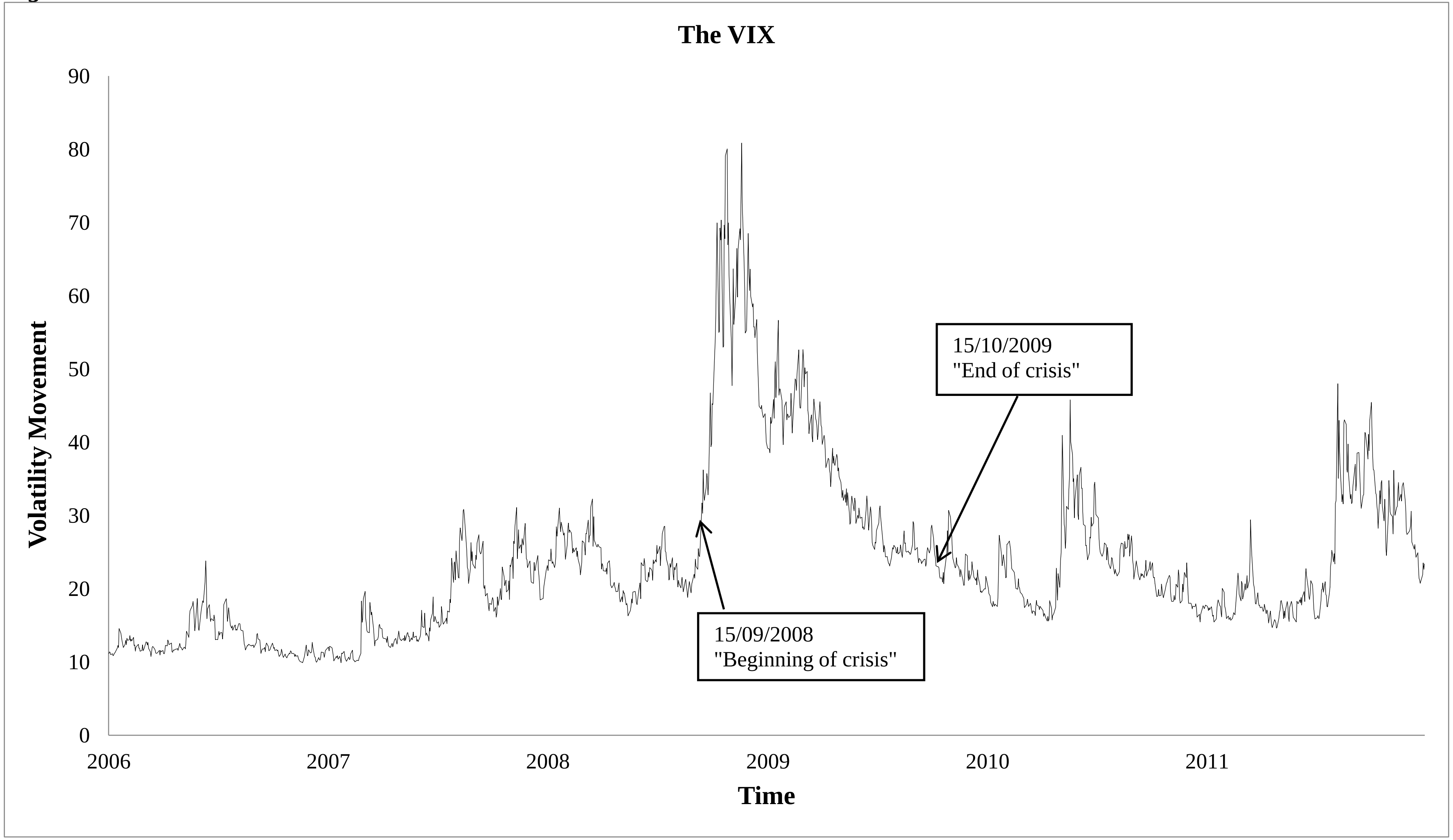
Figure 3.1 shows that volatility in the US market increased drastically in September. This period also corresponds with the downturn of major African markets. Figures 3.2, 3.3 and 3.4 are graphical presentations of how some large African markets (Egypt, South Africa and Nigeria) behaved from late 2008 to 2009.

The VIX remained high well into 2009, which is an indication that this particular crisis was not the type of *short sharp shock* modelled previously in the contagion literature by the likes of Forbes and Rigobon (2002), among others. October 2008 saw further crisis measures such as the introduction of the US$700 billion TARP programme in the US to stave off collapse in the banking system and we saw further emergency mergers in this sector (for example, Wells Fargo taking over Wachovia). On 27 November the US government had to rescue Citigroup after speculators drove its share price down 60%. Further afield, in the UK, RBS was rescued by the UK government on 13 October and around the same time HBOS was forced to merge with Lloyds TSB, which ultimately led to the partial collapse and bailout of this bank.

Although the number of new events associated with the crisis diminished somewhat during 2009, it continued to have reverberations well into the year. As can be seen in Figure 3.1 market volatility did not return to close to “normal” until well into the third quarter. Defining the end point of the financial crisis is also open to interpretation but I also used the VIX as a guide. Using the mean index value over a 12-year period from the start of 2000 as a guide, the index is seen to revert back to its average by early October 2009. This gives an indication that market expectations were that the crisis was drawing to a close. Based on this I identify the end period of the *long period contagion event* as 15 October 2009.[8]

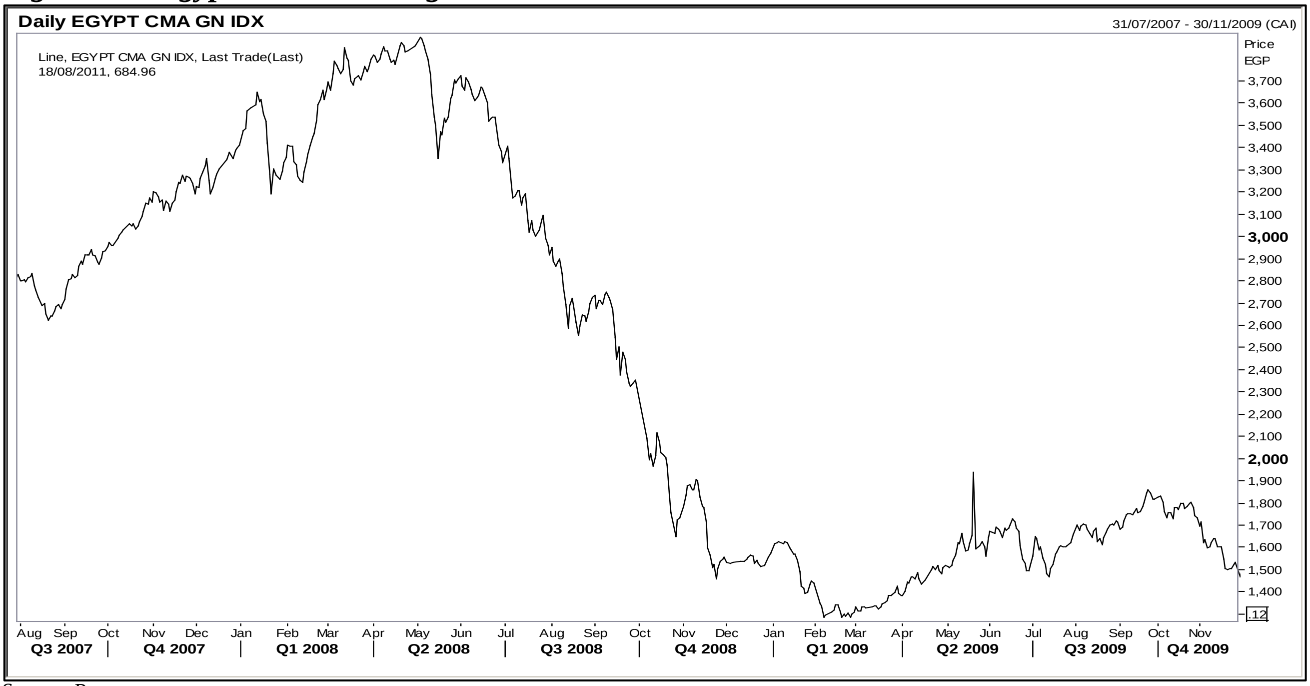
[8] The mean daily closing value of the VIX over the period 03/01/2000-11/05/2012 was 21.72. The index began to show a significant increase above this level from the middle of 2007, peaking at 79.13 on 20/10/2008. It began to revert to the mean value during 2009 and by 15/10/2009 was at 21.72.

Figure 3.1:[9] ***S&P 500 VIX 2006-2012***



[9] Figure 3.1 shows volatility movement on the S&P 500 from 2006 to 2012. Volatility is at the highest from around late 2008 to early 2009.

Figure 3.2: Egypt Stock Exchange

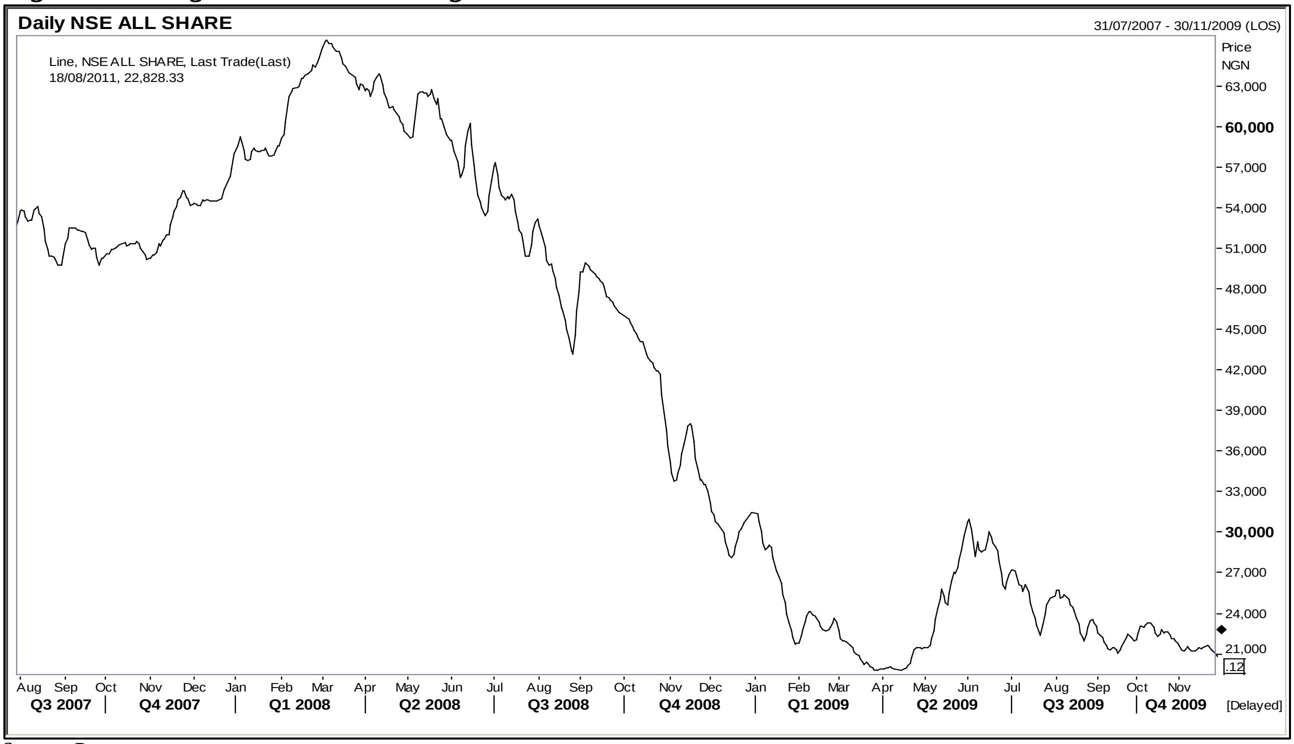


Source: Reuters

Figure 3.3: Johannesburg Stock Exchange

Source: Reuters

Figure 3.4: Nigeria Stock Exchange



Source: Reuters

3.2.1.2 Short crisis periods

Another noticeable characteristic of the selected crisis period above (the long period) are the individual spikes observed in the VIX in Figure 3.1 presented above. This suggests that it may be more appropriate to treat the crisis as *accumulation* of events rather than a single event.

This has implications for the study of contagion from the US to other markets from a behavioural finance perspective. I speculate that we may possibly find evidence of two possible forms of behaviour. First, I speculate that behaviour may reflect a “decision fatigue” effect given that the crisis developed over such a long period. Specifically, I argue that shocks subsequent to the initial Lehman bankruptcy-based shock of 15 September 2008 may possibly result in smaller contagion effects than the initial shock, as investors in overseas markets have become better able to interpret the potential consequences of such events. An alternative second argument is that investor behaviour may show evidence of *representativeness bias* (see Harman 2009). The argument here is that investors would respond to each of the sub-crises in the same way as they see the impact of the previous sub-crisis as representative.

After the Lehman initial shock there was a whole series of further fallout events and a whole series of emergency interventions into the financial markets by regulatory authorities. These are well documented in the historical studies of the crisis.[10] It is, however, difficult to identify the impact of individual events on the market given that many of these were in close proximity. We can, on the other hand, possibly identify the sub-periods in the market when fear within the market spiked by referencing the "gauge of fear", i.e. the VIX.

A number of volatility spikes occurred between October 2008 and November 2008. The first spike was on 10/10/2008 and this was followed about a week later on 17/10/2008 as the market continued to try to understand and accurately price in the potential impact of the crisis. I also identify two further spikes on 27/10/2008 and 20/11/2008.

I test for short-period contagion by comparing the pre-crisis correlation against the first sub-period and against subsequent *cumulative* sub-periods. I will attempt to interpret the reasons for any contagion found from a behavioural perspective. For example, investor decision-making may arguably reflect factors such as *decision fatigue or representativeness bias* and this may manifest itself in the ways that the correlation adjusts from the pre-crisis period to each successive spike.

[10] See for example: http://timeline.stlouisfed.org/. Access date: 5/01/2014.

The sub-periods identified are:

a. Sub-period 1 (15/09/2008-10/10/2008)

b. Sub-period 2 (15/09/2008-17/10/2008)

c. Sub-period 3 (15/09/2008-27/10/2008)

d. Sub-period 4 (15/09/2008-20/11/2008)

The periods highlighted above can be related reasonably closely to the following specific events:[11]

1. "10 October 2008: A global rout starts in Asia as recession fears deepen, with Japan's Nikkei index falling almost 10%, its biggest drop in 20 years. Singapore officially slides into recession. The FTSE 100 plunges more than 10% to 3,932.1 points, falling under the 4,000 mark for the first time in five years. This fall represents the worst daily fall since the crash of 1987 and wipes more than £100 billion off the value of Britain's biggest companies. Oil prices fall US$5 a barrel to a one-year low. The Dow crashes almost 700 points to 7,882 in the first few minutes of trading, a fall of 8%".

2. "17 October 2008: French savings bank Caisse d'Epargne announces a loss of €600 million in a "trading incident", which the bank says was triggered by what it called "extreme market volatility" amid the market crash in the previous two weeks".

3. "24 October 2008: Shares and the pound slump as official government figures confirm that the UK economy is shrinking, with the biggest drop in GDP since 1990. The Ukraine and Hungary seek US$16.5 and US$10 billion rescue packages, respectively, from the IMF. In Denmark, the Central Bank raises its key interest rate by 0.5 percentage points to 5.5%. Stock markets around the world plummet. Investors fear that governments, central banks and finance

[11] Various sources: http://timeline.stlouisfed.org/. Mauro F. Guillén, Access date: 08/06/2014.

ministers will not be able to stop the deepening of a global recession. The Dow Jones opens with a drop of almost 490 points (a 5% drop). Before opening Dow futures drop 550 points, triggering a temporary trading halt in stock futures contracts in an effort to slow the decline".

4. "20 November 2008: The Dow Jones Industrial Average plunges another 445 points in the last minutes of the trading session, closing at 7,552. This is its lowest point in six years. Shares in Citigroup plummet another 26%, with drops of more than 10% in the shares of other major US financial institutions".

Note that in testing the short period affects the same starting point is used (the Lehman's crisis). Although individual sub-periods are identified above, the focus of this thesis is to examine the *cumulative impact* of the crisis in terms of changes in correlations as the crisis period lengthens. I believe this approach will help in the process of exploring the potential importance that behavioural biases may have played in the decisions made by African investors during this period.

Figure 3.5: The VIX showing spikes during the crisis

3.2.2 Countries chosen for study and their market returns January 2007-October 2009

The principle goal of the thesis is to identify any contagion effects between the US and African markets. While the US is a developed market, African markets are a mixture of emerging/frontier markets[12] and non-classified "other markets". The 2007-09 crisis was a global event with repercussions across all market types. It is therefore important for comparative purposes to examine if the contagion events played out in different ways in respect to a representative sample of (i) developed markets and (ii) non-African emerging/frontier markets.

Previous crises examined in the contagion literature have focused on the impact on countries in the same region or markets of the same economic structures and fundamentals. For example, crises such as the US market crash of 1987, the European Exchange Rate Mechanism of 1992, the Mexican economic crisis in 1994, the Asian financial crisis (1997), the Russian financial crisis (1998) and the Brazilian crisis of 1999, which began as spill-over of the East Asian financial crisis of 1997 then later engulfed other Latin American countries. My work differs from these studies as the *global and highly protracted* nature of the 2007-09 crisis enables me to examine these different market types.

[12] I use the MSCI classifications in respect to market types. MSCI describes the equity universe in terms of its "global investable market index methodology". This uses a number of criteria to classify different market types. For example, in respect to MSCI Frontier Markets Indices minimum size and liquidity criteria are used. See: http://www.mscibarra.com/eqb/methodology/meth_docs/MSCI_May13_GIMIMethod.pdf. Access date: 09/09/2013.

3.2.2.1 Crisis market index used in this study

The S&P 500 index is selected as the American index; this index is selected on the basis that it is an index that is reflective of a general cross-section of US stocks (unlike, for example, the NASDAQ and DJIA, which consist of technology stocks and the top 30 industrial stocks, respectively).

3.2.2.2 African markets

This work aims to test for contagion during the 2007-09 financial crisis from the US market to 10 African markets: Botswana*, Cote d'Ivoire***, Egypt**, Mauritius*, Morocco*, Namibia***, Nigeria*, South Africa**, Tunisia* and Zambia***. The African countries chosen for this research are a mixture of emerging (**), frontier (*) and "other markets" (***). It can be noted that a number of markets are omitted from this list, for example Zimbabwe and Tanzania. Markets have been omitted where trading is relatively illiquid and where markets are relatively small and undeveloped (by African standards) in order to maintain robustness in the analysis. The markets chosen can be considered as being relatively risky from a US investor's perspective as they carry additional political, economic and currency risks. They are also (as identified below) a lot less integrated with the US than developed markets. A consequence of this is that there are generally much lower correlations with the US market than we find in respect to developed markets. It might therefore be expected that any contagion effects would be related *predominantly* to investor herding rather than financial integration.

Another interesting feature of the markets chosen is that they are high-growth markets. This is significant from a contagion perspective as previous literature suggests that financial crisis can have a disproportionate impact on high-growth markets. This, in part, is a reflection of the tendency of large developed market investors (such as mutual funds) to rapidly liquidate their emerging/frontier market investments in periods of crisis.[13]

It can be noted that the 1997 Asian crises took place during a phase of rapid growth in South East Asia. These countries were experiencing low debt ratios, rapid growth and stability of exchange rates. Dornbusch, Park and Claessens (2000) reported that aggregate capital flows into five crisis-affected countries (Indonesia, Malaysia, Thailand, the Philippines and the Republic of Korea) in the mid-1990s averaged more than US$40 billion annually, reaching a high of about US$70 billion in 1996. As currencies and stock markets in these countries collapsed, in the second half of 1997, more than US$100 billion was repatriated.

The 2007-09 global financial crisis took place when Africa was growing rapidly. United Nations (2009) reported a rise in net private capital flows to Africa from US$17.1 billion in 2002 to US$81 billion in 2007. Perhaps this is one of the reasons why African markets behaved adversely during the crisis and this may possibly be reflected in contagion-related events.

The number of African stock exchanges increased from eight in 1989 to 23 in 2007 (Massa 2009) and the continent has one of the first regional stock exchanges in the world: the Bourse Régionale des Valeurs Mobilières (BRVM). Established in 1998 and located in Abidjan, Cote d'Ivoire, the bourse links the eight West African French-speaking countries of Benin, Burkina Faso, Côte d'Ivoire, Guinea Bissau, Mali, Niger,

---

[13] See Graciela L. Kaminsky, Richard K. Lyons and Sergio L. Schmukler,(2001) *Mutual Fund Investment in Emerging Markets: An Overview,* World Bank Economic Review 2, 315 – 339.

Senegal and Togo. It is also referred to as the West African Regional Bourse. Another regional market opened in 2003 for the countries of Central Africa with headquarters at Libreville, Gabon. Its member countries include Cameroon, Central African Republic, Chad, Congo, Gabon and Equatorial Guinea.

Most African stock exchanges are members of the African Securities Exchanges Association (ASEA). ASEA is composed of 22 exchanges (Bolsa de Valores de Cabo Verde, Bolsa de Valores de Moçambique, Botswana Stock Exchange, Bourse de Casablanca, Bourse de Tunis, Bourse Régionale des Valeurs Mobilières de l'Afrique de l'Ouest, Dar-Es-Salaam Stock Exchange, Douala Stock Exchange, Egyptian Exchange, Ghana Stock Exchange, JSE Ltd, Khartoum Stock Exchange, Libyan Stock Market, Lusaka Stock Exchange, Namibian Stock Exchange, Nairobi Stock Exchange, Nigerian Stock Exchange, Malawi Stock Exchange, Uganda Securities Exchange, Stock Exchange of Mauritius, Stock Exchange of Swaziland and Zimbabwe Stock Exchange) in 27 countries (Benin, Botswana, Burkina Faso, Cape Verde, Côte d'Ivoire, Egypt, Ghana, Guinea Bissau, Kenya, Libya, Mali, Malawi, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Senegal, South Africa, Sudan, Tanzania, Togo, Tunisia, Uganda, Zambia and Zimbabwe).

Table 3.1 below lists the selected active stock exchanges. All the exchanges in the table are members of the ASEA. The listed exchanges are quoted as the most active stock exchanges in Africa by UNDP's African Stock Markets Handbook (2003).

Table 3.1: African Stock Markets under study

Countries	Name of stock market	Index	Opened/established	Reuters index code
Botswana	Botswana Stock Exchange	BSE Domestic	1989	.DCIBT
Côte d’Ivoire	Abidjan SE Composite Index	Bourse Régionale des Valeurs Mobilières (BRVM)	1998	.BRVMCI
Egypt	The Egyptian Exchange	EGX	1883	.CCSI
Mauritius	Stock Exchange of Mauritius	SEMDEX	1989	.MDEX
Morocco	Casablanca Stock Exchange	CSE	1929	.MASI
Namibia	Namibian Stock Exchange	NSX	1992	.OVRLNM
Nigeria	The Nigerian Stock Exchange	NSE	1960	.NGSEINDEX
South Africa	Johannesburg Stock Exchange	JSE	1887	.JALSH
Tunisia	Tunis Stock Exchange	TSE	1998	.TUNINDEX
Zambia	Lusaka Stock Exchange	LuSE	1993	.ALSLZ

Source: UNDP handbook 2003, ASEA year book 2009:2008:2007 and Reuters

Daily returns of all the African markets under study are provided in Figures 3.6 to 3.8. The shaded elements of the charts reflect the crisis period. The data sources are identified in Section 3.2.3 below.

It is immediately evident that several patterns exist among these markets. Morocco, Nigeria and South Africa exhibit high volatility throughout the period with significant increases during the crisis period. Botswana, however, appears more volatile before the crisis period while Mauritius and Egypt show relatively low pre-crisis volatility, which increases significantly in volatility during the crisis. Cote d’Ivoire shows an important example of why researchers need to be very careful when modelling with this type of data. The almost straight line with a sudden increase and drop during the crisis period reflects a long period of missing data that my subsequent analysis has to adjust for.

Figure 3.6: Daily returns on African stock markets, January 2007- October 2009 (shaded portion is the crisis period; 15/09/08-15/10/09)

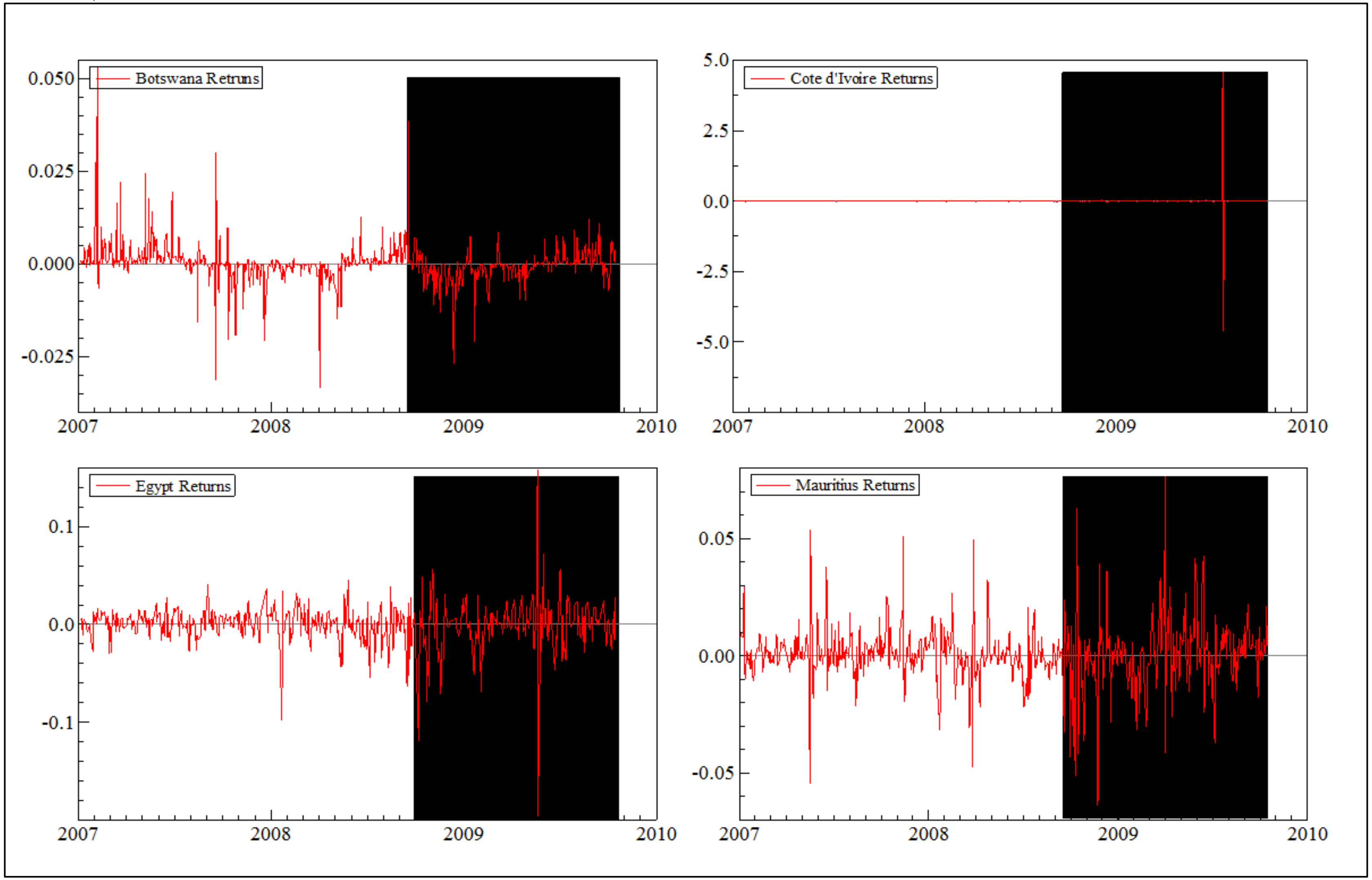


Figure 3.7: Daily returns on African stock markets, continued

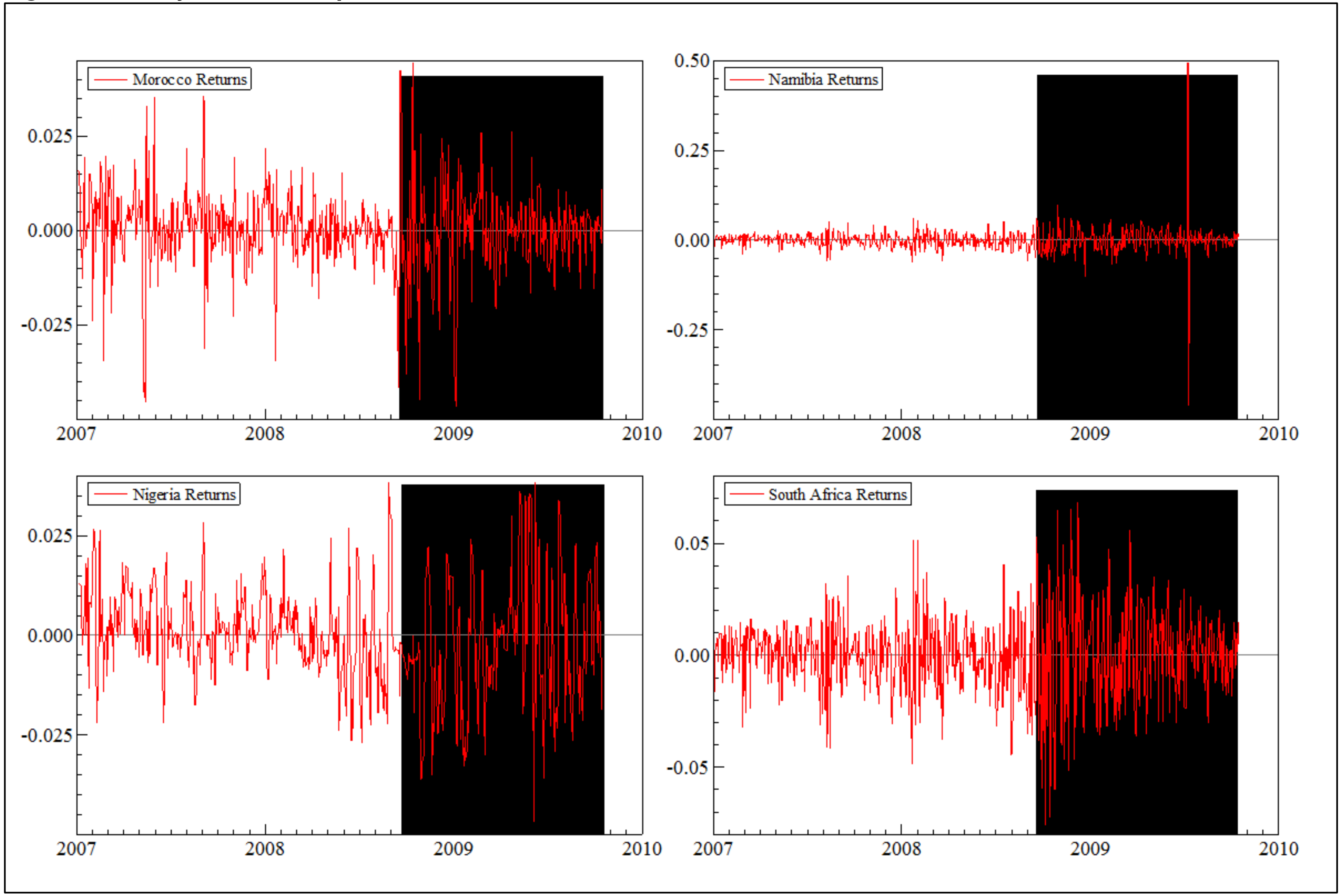
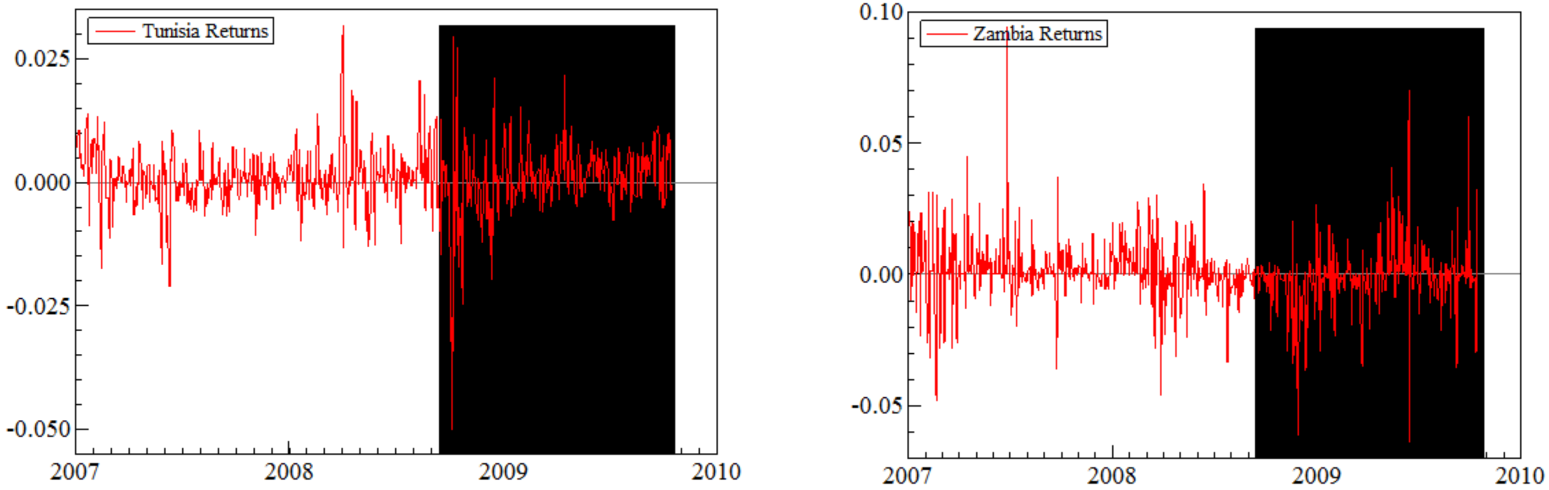


Figure 3.8: Daily returns on African stock markets, continued



3.2.2.3 Developed markets

Financial institutions in developed country markets suffered greatly due to exposure to the US sub-prime mortgages and its knock-on effects. Investment banks and banks with large investment arms (Bear Sterns; Lehman Brothers, RBS, BNP Paribas, IKB Industriebank) across the US and European countries were bailed out, while some were subsequently taken over (for example, Merrill Lynch). In such circumstances it might be expected that any contagion event would be related *predominantly* to the *integration* between institutions in these markets rather than herding.

The developed markets sample countries used in my study consist of Canada, France, Germany, Italy, Japan, Spain and the United Kingdom. Table 3.2 gives information on the sample markets and their Reuter's index code at the time of the research.

Figures 3.9 and 3.10 provide a graphical presentation of the daily returns of the developed markets. It is clear from the figures that volatility in the markets increased during the crisis period (shaded portion). France, Germany, Italy, Japan and Spain demonstrated some large negative returns at the beginning of 2008 with Germany (Figure 3.9) producing the largest negative return. The charts also illustrates decline in volatility towards the end of 2009 especially in the UK. Also, the graphical presentations in Figures 3.9 and 3.10 show that Canada and the UK are more stable than other developed markets before the crisis period. The data sources are identified in Section 3.2.3 below.

Table 3.2: Developed stock markets under study

Countries	Name of stock market	Index	Founded/established	Reuters index code
Canada	Toronto Stock Exchange 300 Composite	TSX	1861	.GSPTSE
France	Euronext Paris	CAC 40 Index	1987	.FCHI
Germany	GER Deutsche Boerse	DAX Index	1988	.GDAXI
Italy	Milan Stock Exchange	BCI General Index	1808	.BCII
Japan	Tokyo Stock Exchange	NIKKEI 500 Index	1949	.N500
Spain	Madrid Stock Exchange	Madrid General Index	1985	.SMSI
UK	London Stock Exchange	FTSE 350	1801	.FTLCS

Source: Reuters and various indices websites

Figure 3.9: Daily returns on developed stock markets (shaded portion is the crisis period; 15/09/08-15/10/09)

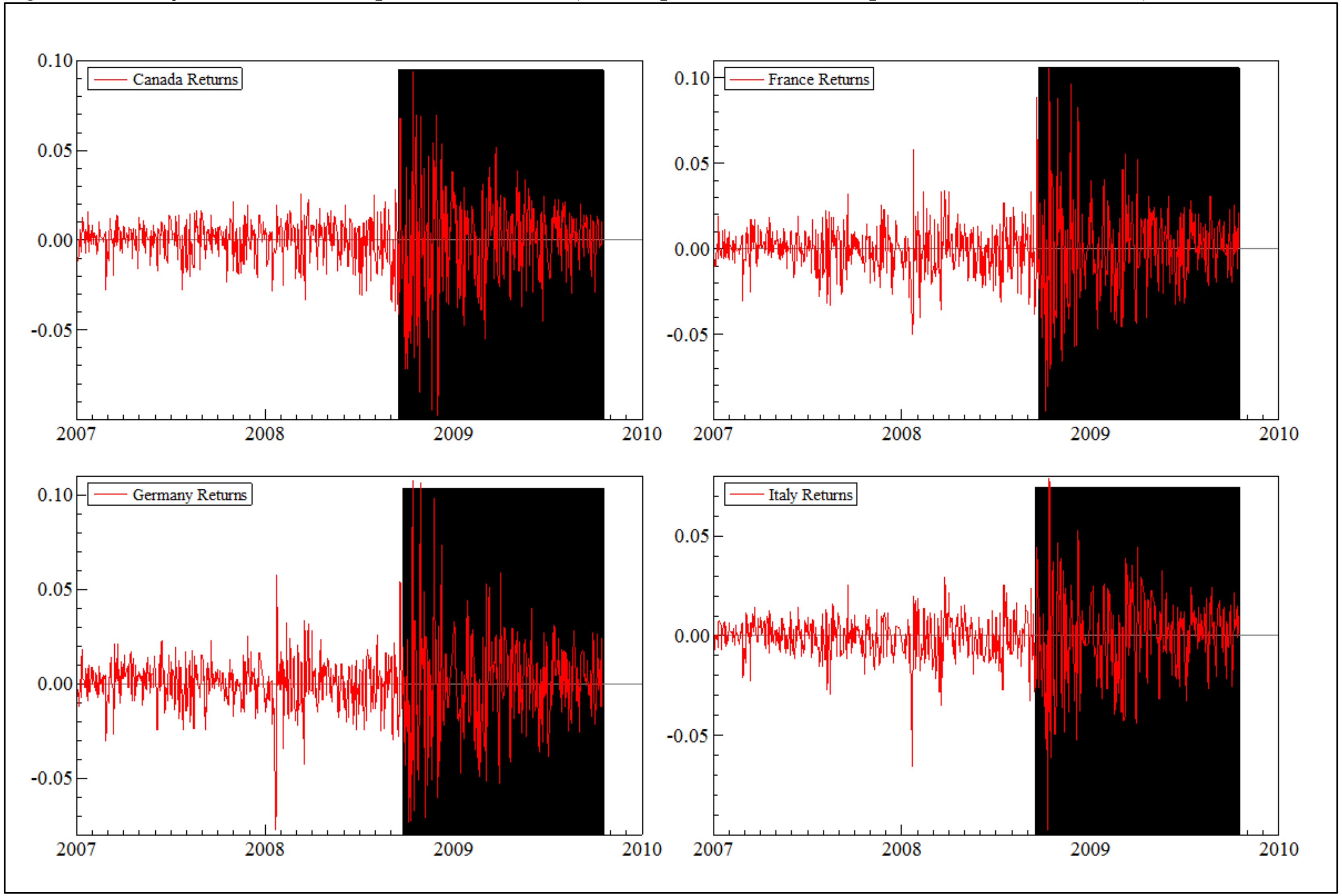
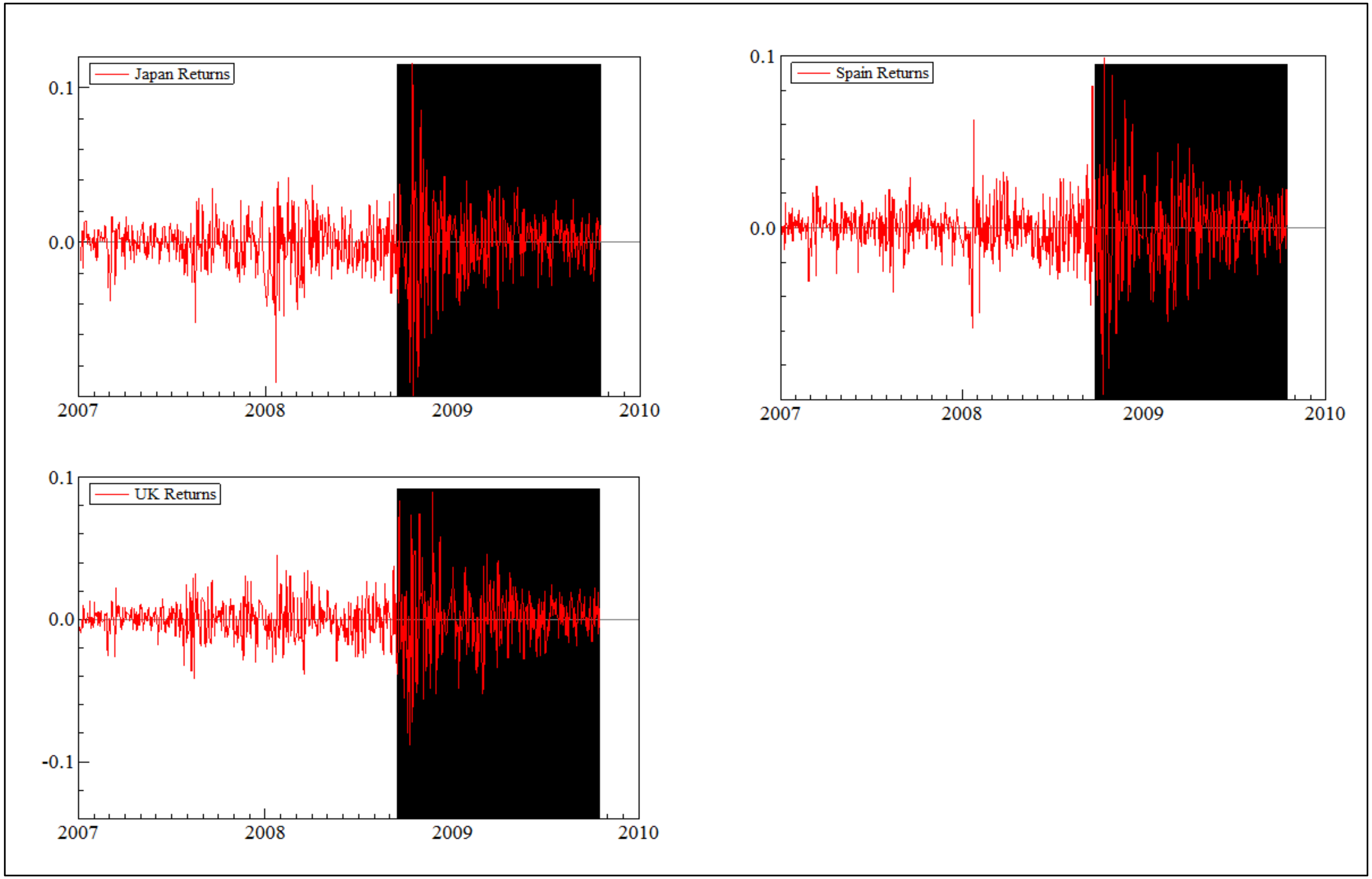


Figure 3.10: Daily returns on developed stock markets, continued (shaded portion is the crisis period; 15/09/08-15/10/09)



3.2.2.4 Comparative (other) markets

China and India are included in the sample for comparative purposes as they represent two of the fastest-growing emerging markets. India, for instance, has enjoyed an impressive growth rate of 9% per annum. This is reported as the fastest in history along with China (Sharma 2014).

Table 3.3 below provides a profile of the comparative markets and the Reuter's index code of the respective indices as at time of research.

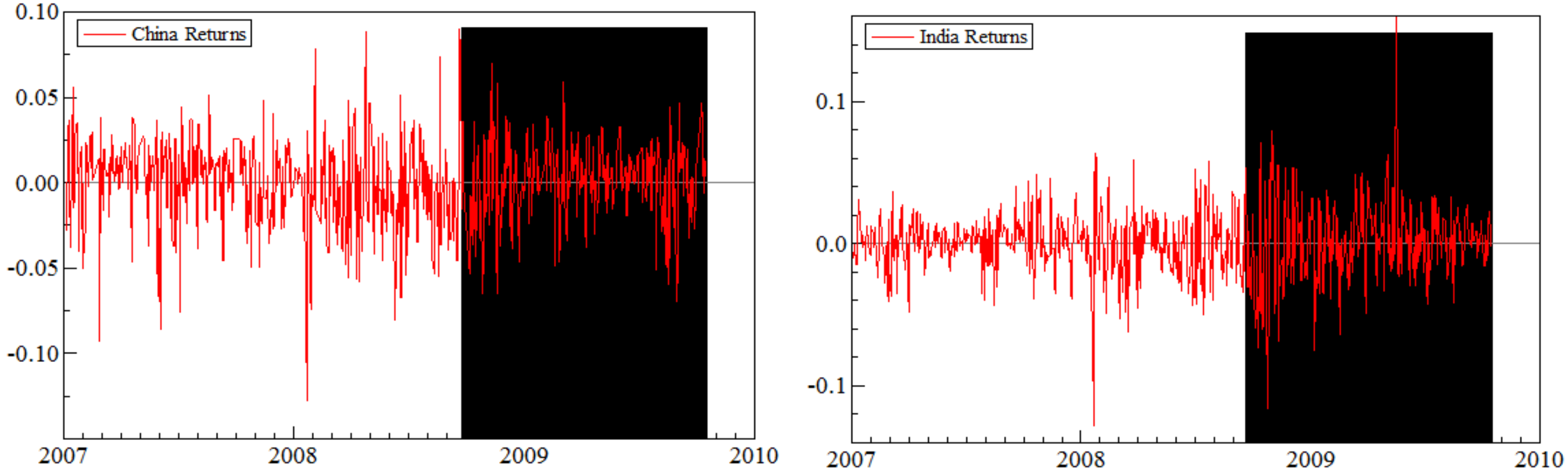
Graphical presentation of the daily returns of these markets is provided in Figure 3.11 below. While China shows greater volatility before 2009, India's volatility is higher after 2009. As identified in the developed markets above, the comparative markets also showed high negative returns in the beginning of 2008. China demonstrates higher volatility than India in the stable period (non- shaded portion). China's volatility during crisis did not show much difference from what is observed in the market during stability except in a relatively short period before the onset of the crisis period. India on the other hand shows more volatility during crisis as compared to its stable period. However, China seems to be the more volatile of the comparative markets. The data sources are identified in Section 3.2.3 below.

Table 3.3: Other stock markets under study

Countries	Name of stock market	Index	Opened/established	Reuters index code
China	Shanghai Stock Exchange A Share Index	SSEASI	1990	.SSEA
India	Bombay Stock Exchange	BSE	1875	.BSESN

Source: Reuters

Figure 3.11: Daily returns comparative markets (shaded portion is the crisis period; 15/09/08-15/10/09).



3.2.3 Data set

The data used is the daily closing values of stock markets obtained from the Thompson-Reuters Eikon Financial Database shown in local currencies. The indices used are the principal indices from the respective countries (see Tables 3.1 and 3.2 for details in respect to their RIC codes).

Eikon did not have a full data set on all major African countries and although another major source was available (MSCI) this data set posed a number of reliability issues[14] and was eventually discounted as a potential source.

The Eikon financial database only guarantees two years of daily data. Although most indices can go back significantly longer periods, the full data required for two major African markets (Kenya and Ghana) was not available from Eikon or other sources available from the university. These countries are therefore omitted from the study. Other countries omitted from the study include Tanzania (a very illiquid market with only 19 stocks traded), Zimbabwe (limited period of data available), Malawi (limited period of data available), Mozambique (no available data), Swaziland (no available data) and Uganda (not enough data).

Data cleaning issues

Market holidays were the biggest data issue faced in this thesis. National holidays that differ from country to country mean that when US markets are open and trading it is possible for country B markets to be closed. This results in a series of non-

[14] MSCI data is converted into US dollars, which means that the value of the index will change in dollar terms on non-trading days when the respective stock markets were not open. This made it difficult to identify and eliminate non-trading days from the data set, which meant that this was discounted as a source.

corresponding dates across the raw market data. *A lot of time was taken in data cleaning going through each data set and deleting the non-corresponding dates manually.*

3.3 HYPOTHESIS AND MODEL DEVELOPMENT

As identified in Section 3.2, the financial crisis was long, drawn out and contained a series of sub-events. The 2007-09 crisis can be contrasted with previous events examined in the contagion literature. These can be characterised as being more in terms of one-off short period events that rarely have an impact on the markets for more than three months. Examples of short crises papers are presented in Table 3.5 below.

Table 3.4: Examples of short-term contagion studies

Authors	**Duration of crisis period studied**
Forbes and Rigobon (2002)	1) 1997 East Asian Crisis: 1 month 2) 1994 Mexican Peso Crisis: less than a month 3) 1987 US Stock Market Crash: 1 to 2 months
Asongu (2011)	04/01/2008-29/01/2008: less than a month
Collins and Biekpe (2003)	20/10/1997-28/11/1997: just over a month

The 2007-09 crisis was not a single short, sharp shock but a series of sub-events that unfolded in the US over a period of more than a year (see Section 3.2 above). I therefore test for contagion from two main perspectives:

(i) Characterising the crisis as a single event (Hypothesis 1)

(ii) Characterising the crisis as a series of sub-crisis events (Hypothesis 2)

The two groups of markets in this research (developed and African) differ markedly in their financial infrastructures as well as their level of financial integration with the US. This is self-evident from constant correlations estimates over the stable period (01 January, 2007 to 14 September 2008). Correlations between the US and most African markets (see Table 3.5) are very low and sometimes negative (the case in Nigeria and Zambia). South Africa is the only African market with a high correlation with the US, providing up to 42% (0.42468). All the developed markets in the table provided high correlation values with the US.

Table 3.5: Demonstrating the degree of relationship by means of raw correlations

African markets	Correlation between the US and each country over the period 01 January, 2007 to 14 September, 2008
Botswana	-0.01398
Côte d'Ivoire	-0.05424
Egypt	0.13112
Mauritius	0.00929
Morocco	-0.02654
Namibia	0.34109
Nigeria	-0.04036
South Africa	0.42468
Tunisia	0.12614
Zambia	-0.01493
Developed markets	
Canada	0.65332
France	0.65955
Germany	0.59425
Italy	0.48404
Japan	0.37801
Spain	0.57771
United Kingdom	0.66276
Other markets	
China	0.03576
India	0.26606

I cite this evidence as the justification for expecting that there may be differences in the degree (and possibly form) of contagion between the two groups. On this basis I split the principle hypotheses below into two sub-categories, namely, developed and African markets, in order to identify any differences.

<u>Hypothesis 1</u>

The principle hypothesis is that contagion occurred during the full period of the 2007-09 financial crisis. This is formally tested as:

Hypothesis 1a: There is a statistically significant increase in correlations between US and developed markets over the period 15/09/2008-15/10/2009.

Hypothesis 1b: There is a statistically significant increase in correlations between US and African markets over the period 15/09/2008-15/10/2009.

<u>Hypothesis 2</u>

The secondary hypothesis is that the crisis developed as a series of sub-crises (see Section 3.2.1.2 above) and that contagion events occurred in each of these sub-periods. This is formally tested as:

Hypothesis 2a: There is a statistically significant increase in correlations between US and developed markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

Hypothesis 2b: There is a statistically significant increase in correlations between US and African markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

As stated in the last paragraph of Section 3.2.1.2, the impact of the crisis will be tested as a cumulative effect. For example, I did not test the stable period against sub-period 3 on its own, I tested it against the cumulative effects of sub-period 1-3.

The spread of financial crisis: a hypothesised framework model

The examination of the data in Section 3.2 and correlations estimated in Table 3.5 indicate to me that contagion events from a developed market to another developed market are likely to be very different from a contagion event from a developed to an emerging/frontier market. Using this finding and also existing theoretical literature on contagion discussed in Chapter 2 to provide insights regarding the model in explaining contagion in the two groups of markets in this thesis, I now present a hypothesised provisional model of contagion (shown in Figure 3.12).

There are a number of hypotheses that could explain the spread of shocks across countries (Chapter 2). The low correlations with Africa (shown in Table 3.5 above) suggest that the *linkages* between US and African markets are relatively weak.

The higher correlations with developed markets probably reflect the stronger linkages between their financial institutions. For example, we see that global investment banks' financial intermediaries have major presence in most of the world's financial centres. We only need to look at the international nature of banks and institutions in London to see this.[15] From this I would argue that any contagion effect would be *predominantly* financial market integration-based.[16] A caveat that can be added is that I am not excluding the possibility that some herding behaviour might have also occurred during this period. This could, for example, reflect *anchoring* type behaviour of investors in times of extreme uncertainty.

The principle mechanisms by which a financial crisis is transmitted between markets are shown in Figure 3.12 below as *contagion*, *interdependence* and *spill-over*. Forbes and

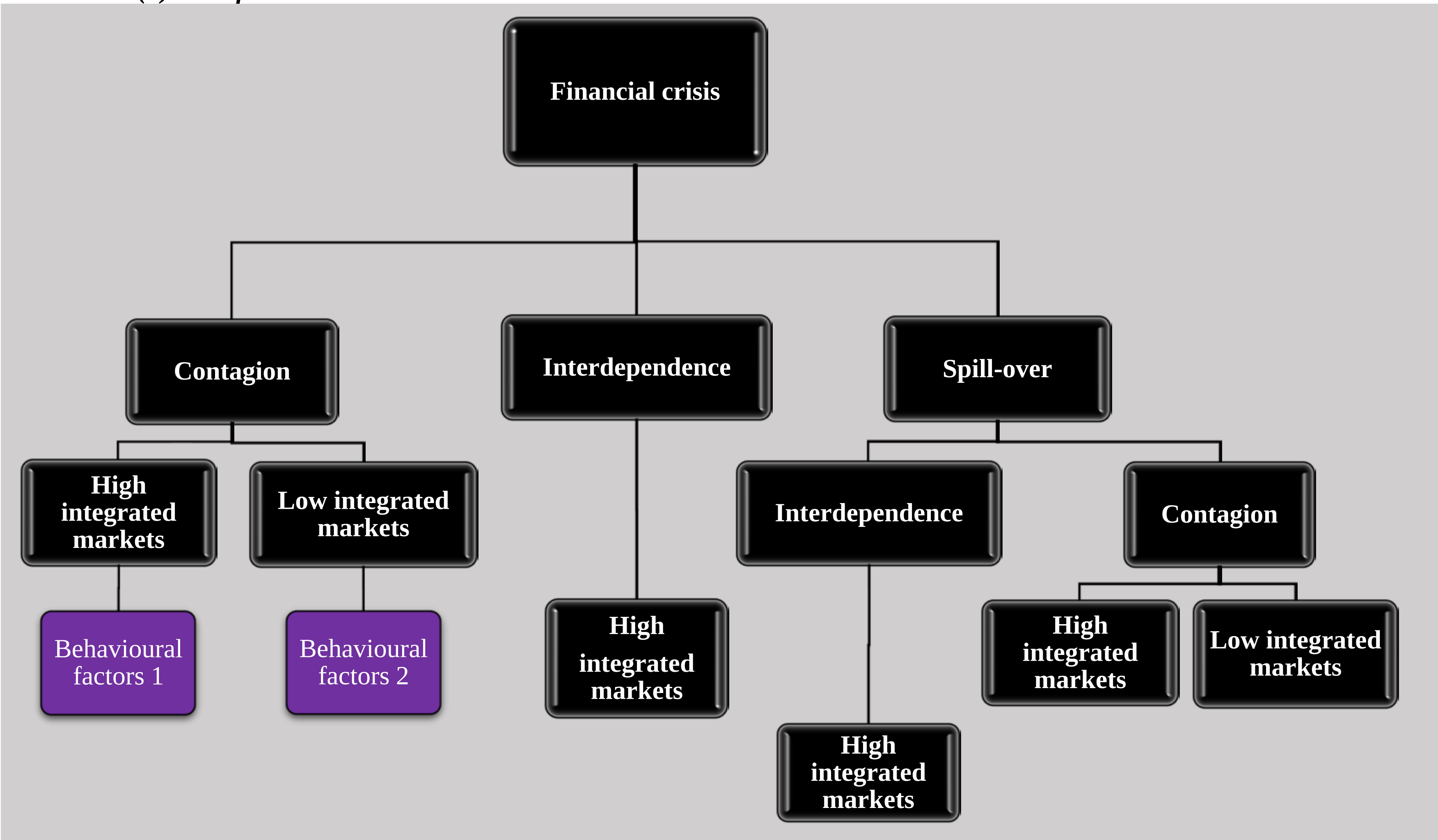
[15] See for example: http://www.cass.city.ac.uk/__data/assets/pdf_file/0019/124930/CBR-WP01-12.pdf

[16] This does not mean of course that any herding effect can be entirely discounted.

Rigobon (2002) argue that both contagion and interdependence result in increases on correlation but that a contagion event results in a relatively *bigger* increase. They are differentiated in terms of statistical significance. An increase that is statistically significant at 5% identifies contagion. If it is not significant at 5% it identifies interdependence. In effect the distinction is based on the extent to which the correlation increases.

As stressed by Massacci (2007:2): “The distinction between interdependence and contagion is of interest to policy makers (either in international financial institutions, such as the IMF, or at central banks) and to profit maximisers investors. In the former case, if a random jump from a *good* to a *bad* equilibrium (that is contagion) occurs, then a policy intervention could be effective; conversely, in the case of interdependence a similar action is unlikely to have any significant effect. In the case of investors, the exposition to market risk can be generally reduced by portfolio diversification; however, if contagion occurs then the degree of dependence between markets increases, and portfolio diversification may not be an effective strategy to follow. Therefore, because of the different effects they have on economic agents’ decision process, the identification of interdependence and contagion effects has to be achieved”.

Figure 3.12: Forms of financial crisis: A preliminary model of contagion based on the expected relationships between (i) US-developed markets and (ii) US-African markets



Financial crisis can also have a *spill-over* effect. It essentially implies a lagged impact of other country-specific effects that arises as a result of economic linkages between countries, for example, through trading arrangements (Dungey and Martin 2000:3). In my thesis, spill-over is defined as a situation whereby one market within a region is affected by the crisis of a developed market and *then* subsequently transmits the crisis to other markets within the region (e.g. from the US to South Africa and then from South Africa to "other" African markets.

I argue that the existence of sub-crisis periods in the 2007-09 crisis may be important in the spread of the crisis and that behavioural finance theory is likely to play an important role in explaining this transmission process. This is because as investors get used to a series of events their reactions may change in response to each subsequent event. Behavioural finance theory would suggest to us that uncertainty is the key driver of behaviour during crisis situations. The question arises from a behavioural perspective of how will market participants in the markets of other countries respond? Will they treat each sub-event as separate and unrelated and *anchor* their decisions on the US market in each instance? Will they become used to crisis in the US and stop responding to events in the US altogether? Or will each sub-crisis in the US have a diminishing impact on these markets? These are issues I examine in this thesis in Chapter 6.

3.3.1 Expectations

Given the dominant position that the US holds in world financial markets, a crisis that originates in this market can easily affect other nations through either financial integration or herding behaviour on the part of investors.

US and African markets have few similarities in terms of size or structure. However, major falls in some African markets during the financial crisis led us to ask if growing market integration played a role. Nellor (2008) reported the steady integration of African markets with the global financial systems, in particular Sub-Saharan Africa – the rapid inflow of foreign capital saw foreign trading in African (excluding South Africa) debt markets more than triple in 2007 compared with 2005.

The US has strong financial links with other developed countries, as was evidenced by the fact that rescue plans for financial institutions were needed not just in the US but in many developed countries. Therefore it is highly plausible that financial integration played a part in the transmission relationships. The importance of integration in the spread of financial crisis is a major theme in the academic literature (see Wongswan 2003, Gilmore and McManus 2002, Patev and Kanaryan 2003, and Bekaert, Harvey and Ng 2005).

My expectations are summarised as follows:

1. Evidence of contagion is expected during the 2007-09 financial crisis in African markets both in long and short sub-crisis periods,
2. Evidence of contagion or interdependence is expected during the 2007-09 financial crisis in developed markets during both long and short sub-crisis periods,
3. There will be substantial differences between emerging and developed markets respond to the financial crisis because of market linkage differences. Expectations are that integration effects will explain any US/developed market contagion while herding behaviour might explain any contagion found in emerging/frontier African markets.

3.4 METHODOLOGICAL NOTES

Having identified issues associated with the data and having identified the hypotheses to be tested, in this section I now examine how these issues will influence the statistical methodology applied in the thesis. This section is divided into two:

1. Identifying the major statistical approaches available to test for contagion,
2. Justifying the selected approaches used in this thesis.

3.4.1 Statistical approaches of contagion

The different approaches of contagion testing were identified by Rigobon (2001) and then further classified by Forbes and Rigobon (2002) into four principle methodologies. These are identified in Table 3.6 below along with examples found in the academic literature.

Table 3.6: Contagion testing frameworks

METHODOLOGY	**MAJOR PAPERS**
1) Correlation Coefficient Analysis	King And Wadhwani (1990)
	Lee and Kim (1993)
	Forbes and Rigobon (2002)
	Caporale, Cipollini and Spagnolo (2005)
2) DCC-ARCH/GARCH	Engle (2002)
	Chiang, Jeon, and Li (2007)
3) Cointegration Technique	Longin and Solnik (1995)
	Kanas (1998)
4) Transmission Mechanism Approach	Eichengreen, Rose, and Wyplosz (1996)
	Forbes (2004)

Categorisation from Forbes and Rigobon (2002), Wang and Thi (2006), Lee, Wu and Wang (2007) and Cheung, Tam and Szeto (2009)

Cross-market correlation analysis

The most popular contagion methodology found in the contagion literatures is based around this approach. This forms the basis of the contagion model based on correlation coefficients modelled by King and Wadhwani (1990), further developed by Forbes and Rigobon (2002) and more recently by Caporale et al. (2005). This test is based on changes in correlation coefficients between markets before and after a shock. If the correlation coefficients increase by a statistically significantly amount after crisis, contagion is said to have occurred. Forbes and Rigobon (2002) can be considered as a seminal article in the early contagion literature. It employs a vector autoregressive (VAR) methodology that controls for non-contagion-related factors by correlating the residuals from two VAR equations. This approach requires an adjustment to be made to the estimated correlation coefficient to take into consideration differences in the volatility in the crisis and non-crisis periods. The impact that the adjustment made on the robustness of the analysis is an issue that is widely discussed in the literature and that will be discussed in detail in the next chapter.

Dynamic conditional correlation analysis

An additional disadvantage of the cross-market correlation model is that estimates are based on single constant correlation estimates. This does not allow the researcher to explore the impact of the crisis on a dynamic basis. The dynamic conditional correlation (DCC) model in contrast estimates individual estimates of correlation at each point in time. The generalised autoregressive conditional heteroscedasticity (GARCH) approach has been used widely to analyse volatility properties of time series data. The variance-covariance transmission mechanisms between countries are estimated using the conditional covariance and the conditional variance at each point in time. This framework was popularised by Engle (2002), who proposed the DCC multivariate GARCH model. It has been popularised, and developed further in a contagion context, by a number of researchers including Chiang, Jeon and Li (2007) who studied the Asian markets from 1996 to 2003.

Cointegration testing

Cointegration testing predates the introduction of DCC. This test has been widely used to examine market interdependencies or the international integration of financial markets. The procedure entails checking for changes in the cointegrating vector between markets in the long run, instead of short run changes after a shock. There are two principle approaches to cointegration; the Engle-Granger two-step approach and the Johansen[17] procedure. There are issues in respect of the statistical power of the test statistics associated with these tests. Another issue is that these tests focus on the long-run relationships between series, which may be problematic if the contagion event is short-lived. It has been argued by Forbes and Rigobon (2002) that the long time frame might miss periods of contagion when correlations increase briefly after a crisis. Longin and Solnik (1995) used this procedure to measure the correlations of monthly excess returns from seven countries over the period 1960 to 1990. They found an increase in correlation between the markets and that the correlation rises in periods of high volatility. Forbes and Rigobon (2002) argue that this technique does not explicitly test for evidence of contagion and as a consequence rejected it.

[17] Johansen, Søren (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica* 59(6): 1551–1580.

Transmission mechanism identification

Rather than focusing on the impact of the contagion event on the *strength of the linkage* between markets, this methodology attempts to identify the ways in which shocks are transmitted across countries. This is based on the assumption that the crisis is transmitted through the integration linkage between countries. These transmission pathways can take a series of forms: for example, through financial market links or through trade relations. This approach employs a variety of statistical techniques to model these relationships. These use a variety of techniques including limited dependant variable type analysis (logit and probit regression), OLS and principal component analysis (Rigobon 2001, Dungey et al. 2005b, Wang 2004, Yang and Lim 2004 and Billio and Pelizzon 2003). Researchers investigating contagion to identify the transmission mechanism look at the size of the estimation parameters to evaluate channels of contagion. Eichengreen et al. (1996) applied the binary probit model on quarterly panel data from 20 industrialised countries to check whether the probability of crisis occurring in a country at a particular time is correlated with crises in other countries at the same time. They reported evidence of contagion (their model controlled for political and economic fundamentals). The tests they implemented suggested that the probability of crisis occurring in one country is correlated with concurrent speculative attacks occurring in other countries. It is also suggested that contagion is more easily transmitted between countries that have strong international trade linkages than to countries with similar macroeconomic circumstances.

A further example of this approach is provided by Forbes (2004). In an extensive study of how the Asian and Russian crises affected different firms around the world. Forbes (2004) used firm-level data set of financial statistics, industry information, geographic data and stock returns for more than 10,000 companies from 46 countries. The study adopted the event-study methodology to investigate if the firms' vulnerability to the two crises studied were affected by factors such as industry, international exposure, debt ratios, trading liquidity and geographic location. Forbes (2004) found that trade linkages (product competitiveness and income effects) were the main predictors in the international transmission of the crises.

3.4.2 Selecting thesis statistical methods

It can be noted from Section 3.3 that my hypotheses focuses on examining differences in the impact of the crisis on the strength of the linkages from the US to Africa and from the US to developed markets. Although I attempt to distinguish between herding and financial market integration effects, I am not attempting to identify the specific integration-related transmission pathways used in the transmission mechanism methodology approach. I therefore discount this methodology.

The following observations can be made:

- First, I note that there is an extensive body of work using a considerable number of different approaches on financial contagion. This suggests that there is no clear-cut best approach.
- Second, as can be recalled in Chapter 2, although there are a number of different definitions of contagion, Forbes' and Rigobon's (2002:2250) concept of ***shift-contagion*** appears to have broad acceptance in the literature (defined as "a significant increase in cross-market linkages resulting from a shock hitting one country or group of countries").

- Third, there are a number of critiques in the literature of Forbes' and Rigobon' (2002) VAR-based methodology.
- Fourth, the 2007-09 crisis was quite unlike previous crises examined in the literature given its long duration.

In my work I will use Forbes' and Rigobon's (2002) narrow definition as it has two important advantages:

1. It provides a direct test for contagion by comparing cross-market correlation coefficient between two countries during a period of stability and after a crisis/shock.
2. The second advantage of the narrow definition is that it provides a direct approach of distinguishing between contagion theories, such as those predicting a change after a crisis or those based on the continuation of the existing relationship between markets after a shock (recall the theories of contagion given in Section 2.3 of Chapter 2).

A correlation of 40% and above during a period of tranquillity would be interpreted as a strong positive correlation. This will serve as a guideline for the interpretation of the relationships between markets before the onset of the crisis. Goetzmann, Li and Rouwenhorst 2004 carried out a long term correlation study which covered the years 1850- 2000 in respect to US markets. They identified that between 1972-2000 correlation between US and what they described as core markets (UK, Germany and France) rarely fell below an average of 40%. This is therefore what I use to define high correlation levels.

After noting that the VAR approach of Forbes and Rigobon (2002) has a number of criticisms in the literature, I have decided that for *robustness purposes* I will employ both the cross-market correlation analysis approach and also the DCC-based approach. This will enable me to make a full comparison of the two methodologies. I also note that contagion testing over a long crisis period has not been extensively examined in the literature. By applying two different methodologies I will have greater flexibility if any modelling issues arise. I also believe that it is important to examine the dynamic impact on correlation of the crisis event. This is particularly important in respect to the 2007-09 crisis because of its length and its sub-phases. It is often commented that the use of averages can obscure a lot of significant information. Estimating the correlation on a dynamic day-by-day basis will enable me to more fully explore changes in the impact of the crisis on correlation linkages over time.

3.5 FOLLOWING CHAPTERS

In Chapter 4, I will test the hypotheses identified using the Forbes and Rigobon (2002) constant correlation analysis along with variations and extensions of it. This analysis will then be repeated for comparative purposes in Chapter 5 using the dynamic correlation methodology before the results are discussed and conclusion drawn about the nature of the 2007-09 contagion events in Chapter 6.

4 CONSTANT CORRELATION BASED CONTAGION TESTING

4.1 INTRODUCTION

This chapter applies non-time-varying *correlation coefficient analysis* using methodologies based on the work of Forbes and Rigobon (2002). This is used to test for the occurrence of contagion from (i) the US to emerging/frontier African markets and (ii) from the US to developed markets during the 2007-09 financial crisis.

The two hypotheses tested, as justified and identified in Chapter 3, identify potential "long period" and "short period" contagion events. The hypotheses tested are:

<u>Hypothesis 1</u>

Hypothesis 1a: There is a statistically significant increase in correlations between US and developed markets over the period 15 September 2008-15 October 2009.

Hypothesis 1b: There is a statistically significant increase in correlations between US and African markets over the period 15 September 2008-15 October 2009.

<u>Hypothesis 2</u>

Hypothesis 2a: There is a statistically significant increase in correlations between US and developed markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

Hypothesis 2b: There is a statistically significant increase in correlations between US and African markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

In this chapter, I test three versions of the constant correlation contagion model. This is done for two principle reasons. First, the extended length of the crisis means that the standard Forbes and Rigobon (2002) methodology can be adjusted in a way that addresses a key criticism of their methodology; namely, in respect to the adjustment they made to the estimated correlation coefficient. The second reason is for robustness. I believe that the combination of these two factors means that my work in this chapter can be considered as being a “novel” contribution to the academic literature in this area.

The three versions of the constant correlation contagion model tested are:

- The base case of Forbes and Rigobon (2002) based on a single VAR system methodology;
- An adjusted Forbes and Rigobon model that uses raw log returns data rather than the residuals from a VAR system;
- A two-VAR system methodology (which therefore does not require an adjustment to the measurement of correlation).

In Section 4.2 the different methodologies applied are discussed. This is followed in Sections 4.3 by a presentation of correlation estimation results and in Section 4.4 by a presentation of contagion test results. Finally, Section 4.5 concludes the chapter with some thoughts about the relative merits of the different methodologies examined.

4.2 DISCUSSION OF METHODOLOGIES

The three methodologies identified above are now considered in more detail.

4.2.1 The single VAR approach

Forbes and Rigobon (2002) developed a restricted single-system vector autoregressive (VAR) based methodology that estimated the correlation between the *residuals* of a two-equation VAR system. In this system the dependent variables are the adjusted daily returns of the two markets being considered. By basing the correlation on the residuals this methodology controls for the lead-lag relationship. This is the impact of previous market returns in the two markets on the returns in the current period. Forbes and Rigobon (2002) used interest rates as an additional explanatory variable in their VAR system but found that omitting the interest rates did not weaken their findings.

They also found the optimal lag structure in the VAR to be five relatively short periods. This is probably a reflection of two factors: (i) that new information tends to be incorporated into financial market processes relatively quickly; and (ii) that the differing opening times of financial markets meant they had to estimate daily returns on the basis of a two-day rolling average.

I have attempted to follow the Forbes and Rigobon (FR) methodology as closely as possible in my work. This has meant basing my VAR system on a five-period lag structure and omitting interest rates as a potential explanatory variable. Tests I undertook in respect to my data identified that these assumptions were credible in respect to my data.[18] I also made use of a two-day rolling average when estimating returns. This was essential given the wide variety of opening times in the markets I am working with. These are shown in Table 4.1 below. The opening times are shown in Coordinated Universal Time (UTC)/Greenwich Mean Time (GMT). As illustrated in Table 4.1, the UK, Spain and Italy begin trading at 08:00AM, UTC. Canada and the US begin at 14:30 UTC. The table shows that there is an overlap of trading hours in Namibia and Morocco. There are also instances where markets' opening times do not overlap at all, such as Japan and the UK or Japan and the US.

[18] It can be noted that in respect to the data used in this thesis, interest rate data were unavailable in relation to a number of African markets, which meant that a full series of tests could not be undertaken.

Table 4.1: Stock markets under view and their opening times

African countries	Index	UTC opening time	UTC/GMT closing time
Botswana	BSE Domestic	07:30	08:30
Côte d'Ivoire	BRVM	09:00	15:00
Egypt	EGX	07:45	13:15
Mauritius	SEMDEX	05:00	09:30
Morocco	CSE	08:00	13:00
Namibia	NSX	08:00	16:00
Nigeria	NSE	09:30	14:30
South Africa	JSE	07:00	15:00
Tunisia	TSE	10:30	12:30
Zambia	LuSE	08:00	10:00
Developed countries			
Canada	TSX	14:30	21:00
France	CAC 40 Index	08:00	16:30
Germany	DAX Index	07:00	21:00
Italy	BCI General Index	08:00	16:25
Japan	NIKKEI 500 Index	00:00	06:00
Spain	Madrid General Index	08:00	16:30
United Kingdom	FTSE 350	08:00	16:30
United States	S&P 500 Index	14:30	21:00
Comparative countries			
China	SSEASI	01:30	07:00
India	BSE	03:45	10:00

Based on the assumptions identified above I now illustrate the single VAR system approach. This is based on the assumption of there being two markets in the system and that contagion is to be tested from Market 1 to Market 2. In this thesis, Market 1 is the US, identified as the origin of the crisis, while Market 2 would represent any of the remaining markets identified in Table 4.1.

Let x represent stock market returns of the US and y the returns of a second country[19] in the following regression:

$$y_t = \alpha + \beta x_t + \varepsilon_t, \qquad (4.1)$$

$$where\ E[\varepsilon_t] = 0; \qquad (4.2)$$

$$E[\varepsilon_t^2] = c < \infty, \qquad (4.3)$$

$$where\ c\ is\ constant\ and\ E[x_t \varepsilon_t] = 0 \qquad (4.4)$$

[19] Where returns are estimated on a continually compounding basis and estimated by ln (x_t / x_{t-1}).

The sample period is divided into two, which FR (Forbes and Rigobon 2002) describes as the *low volatility* and *high volatility (crisis)* periods respectively. They note that the variance will be higher in the *crisis* period and therefore in their single VAR model the measurement of the correlation will need to be adjusted to reflect this.

The VAR system is estimated using the optimal number of lags (identified by FR as five) and containing no exogenous variables (such as interest rates). This is given by:

$$R_t = c + \phi(\mathrm{L})R_t + \eta_t \quad (4.5)$$

$$R_t = \{r_{xt}, r_{yt}\}' \quad (4.6)$$

Where R_t represent the vector of returns, such that r_{xt} is the stock market return in the crisis country (US), and r_{yt} is the stock market return in another country y (an African or alternative developed market), ϕL is the vector of lag and η_t is the vector of reduced form disturbance terms. Given that I am dealing with a two-equation system, the returns equations can, alternatively, be shown in non-matrix format as:

$$r_{xt} = \mu_x + \sum_{k=1}^{m} \alpha_{xk}\, r_{xt-k} + \sum_{k=1}^{m} \beta_{xk}\, r_{yt-k} + \varepsilon_{xt} \quad (4.7a)$$

$$r_{yt} = \mu_y + \sum_{k=1}^{m} \alpha_{yk}\, r_{yt-k} + \sum_{k=1}^{m} \beta_{yk}\, r_{xt-k} + \varepsilon_{yt} \quad (4.7b)$$

The residuals, as identified from the variance-covariance matrix, are then used to estimate the cross-market correlation coefficients for each pair of countries.

The correlation given by the standard definition of correlation is:

$$\rho = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \quad (4.8)$$

where x is the base criterion (in this case US) and y is another market (African or developed).

Forbes and Rigobon (2002) argue that the estimated correlation during the crisis period is generally biased upwards due to the problem of heteroscedasticity (volatility changes in asset returns) in high frequency data. They argue that even if the underlying relationship between x and y does not change, it is possible for ρ to increase whenever the variance of x increases.

Consider the correlations between the returns of two stock markets, to be presented by ρ_1 during the crisis (high volatility) period and ρ_2 during low volatility period. If there is an increase in the volatility of asset return in market 1, the variance in the market will increase, such that $\sigma^2_{x,1} > \sigma^2_{x,2}$. If there is no change to the fundamental relationship between the assets returns in the two markets, then the estimated correlations will be larger during a crisis period than a tranquil period, such that $\rho_1 > \rho_2$. This can therefore give a false indication of contagion given that the increase in correlation is conditional on market volatility. In such cases the estimate of correlation will be biased upward.

Forbes and Rigobon (2002) suggested an adjustment for the heteroscedasticity bias that takes into account the increase in variance during the crisis period. The adjusted correlation is referred to as *unconditional correlation* and is given as:

$$\rho_a = \frac{\rho^{U}}{\sqrt{1+\delta[1-(\rho^{U})^2]}} \qquad (4.9)$$

where

ρ_a = adjusted (unconditional) correlation

ρ^{U} = unadjusted (conditional) correlation, as in ρ in Equation 4.8 above

δ = increase in the variance of x, which measures the change in the period of high volatility against the low volatility period calculated as:

$$\frac{\sigma_{xx}^{h}}{\sigma_{xx}^{l}} - 1, \qquad (4.10)$$

σ_{xx}^{h} = variance during high volatility (crisis period)

σ_{xx}^{l} = variance during low volatility

The unconditional correlation is denoted by ρ_a in Equation 4.9 above. This is the conditional correlation scaled by a non-linear function of the percentage change in the volatility of returns from the country where the crisis started (in this case the US), over the high and low volatility periods.

If there is no change in the underlying relationship between two markets, then the adjustment allows for a levels shift in the volatility of Market 1, whereby $\rho_a = \rho_2$.

Contagion from Market 1 to Market 2 is identified in terms of a significant increase in the unconditional correlation. We therefore are required to undertake a one-tailed statistical test[20].

The null of market *interdependence* is tested against the alternative of *contagion* through the following hypothesis test:

$$H_0 : \rho_a^h \leq \rho^l \qquad (4.11a)$$

$$H_A : \rho_a^h > \rho^l \qquad (4.11b)$$

[20] It was not necessary to adjust the t-test for over lapping periods because the thesis is not looking for significant changes in correlation between the individual short sub-periods. It is instead looking at how correlation changes and testing for contagion between cumulative sub-periods and the stable period. For example, I did not test the stable period against sub-period 2; I tested the stable period against the cumulative impact of sub periods 1 and 2.

ρ_a^h is the adjusted correlation during the crisis period (high volatility).

ρ^l is the correlation during the low volatility period. This period is the full period that consists of the full dataset in the VAR system.

The test statistic that FR developed is identified as following the t-distribution and is estimated as follows:

$$T = \frac{F_h(\rho_a^h) - F_l(\rho^l)}{\sqrt{\frac{1}{N_h - 3} + \frac{1}{N_l - 3}}} \tag{4.12}$$

Where N_h and N_l are corresponding samples sizes of crisis (high volatility) and low volatility periods, F_h and F_l are Fisher's transformations for the high and low volatility period to improve the properties of the test statistics. The Fisher transformation is important because the standard test requires that the coefficients are normally distributed. Fisher's Z transformation provides a solution by converting standard coefficients to normally distributed Z variables.

$$F_h = \frac{1}{2} \ln\left(\frac{1+\rho_a^h}{1-\rho_a^h}\right) \tag{4.13}$$

$$F_l = \frac{1}{2} \ln\left(\frac{1+\rho^l}{1-\rho^l}\right) \tag{4.14}$$

Substituting Equations 4.13 and 4.14 for Equation 4.12 we have;

$$T = \frac{\frac{1}{2}\ln\left(\frac{1+\rho_a^h}{1-\rho_a^h}\right) - \frac{1}{2}\ln\left(\frac{1+\rho^l}{1-\rho^l}\right)}{\sqrt{\frac{1}{N_h - 3} + \frac{1}{N_l - 3}}} \tag{4.15}$$

If the calculated value of the test statistics is higher than the critical value of the one-tailed test at 5% significance, we reject the null hypothesis of *interdependence* in favour of the alternative hypothesis of *contagion.*[21]

[21] This thesis applies the Forbes and Rigobon (2002) definition of contagion. They define an increase in correlation that is not statistically significant at the 5% level as market interdependence. They define an increase in correlation that is statistically significant at the 5% level as contagion. A fall in correlation is not considered.

The model described above is applied in this chapter to test for contagion from the US to (i) the selected African markets, (ii) the selected developed country markets and (iii) selected other emerging markets.

4.2.2 Raw log returns approach

The contagion testing methodology identified in Section 4.2.1 above was repeated using the log returns data rather than the residuals from the VAR. This was undertaken for robustness purposes in order to identify whether or not the control variables used in the VAR (the five-period lagged returns) had a significant impact on the estimated correlation coefficients. The same adjustment is made for heteroscedasticity on the crisis period as in above and the hypothesis is also measured in the same manner.

The aim of this method is to check if the final result will complement the results from a single VAR approach described above. Forbes and Rigobon (2002) argued that variation in the nature of the VAR equation used did not change their final conclusion. By undertaking this test I will be able to identify whether in fact it is also necessary to control for lagged own-market and lagged cross-market affects.

4.2.3 Separate VAR approach

Given that the financial crisis ran over a full year (see Chapter 3 for details), an alternative approach that can be considered is to base the analysis on two separate VAR systems. The advantage of such an approach is that there will be no need to use the adjustment to the correlation measure used by FR. This is because the variances should be relatively homogeneous in the respective VAR systems; there is unlikely to be the step-change in the variance as found in FR *low volatility* and *high volatility* periods. I would expect high variance in the throughout-the-crisis VAR systems and also low variance in the tranquil period VAR system.

It can be noted that the adjustment that FR used has had some criticism in the literature (Billio and Pelizzon 2003) and therefore it can be argued that the results from the separate VAR model will show greater robustness.

This approach[22] splits the full sample data into *tranquil* and *crisis* periods and then runs two separate VAR systems. The residuals from these are then used to estimate the correlations. Hypothesis testing for this variant differs from the method outlined above in that there is no adjustment made to the estimated correlation coefficient. The tranquil or stable period is defined as the period before the crisis and the hypothesis is given as;

$$H_0 : \rho^c \leq \rho^s \tag{4.16}$$

$$H_A : \rho^c > \rho^s \tag{4.17}$$

$where$ ρ^c and ρ^s are correlations of crisis and stable periods. The null of interdependence is tested against the alternative of contagion using t-test as in equation 4.15 above.

[22] Separate VAR tests will only be applied to sub-period 4 and the long crisis period. This is because other sub-crisis periods have relatively small crisis sample sizes to be run through a VAR system separately.

4.3 RESULTS PART 1: CORRELATION ESTIMATION

Section 4.3.1 presents the results of correlations tests undertaken using the three methodologies identified above. The principal features of these results are then described in summary form as stylised facts with the focus being on the differences between the US-African market correlations and the US-developed market correlations.

Section 4.3.2 then presents the results of tests for contagion with the principal features of these results again being described in summary form as stylised facts. Discussion of the results is not undertaken until Chapter 6, given the need to compare them with the time-varying correlation-based contagion tests undertaken in Chapter 5.

4.3.1 Tests undertaken

Correlation estimates are presented below on the basis of three separate methods identified above. These are (i) the base case of Forbes and Rigobon (2002) based on a single VAR system methodology, (ii) the adjusted Forbes and Rigobon (2002) model that uses raw log returns data rather than the residuals from a VAR system and (iii) the two-VAR system.

For each of these three methods, the pre-crisis, stable or low-volatility period and the crisis period or high-volatility period correlations are identified. These relate to models based on the following crisis definitions: (i) long crisis: 15/09/2008- 15/10/2009, (ii) sub-period 1: 15/09/2008-10/10/2008, (iii) sub- period 2: 15/09/2008-17/10/2008, (iv) sub- period 3: 15/09/2008-27/10/2008 and (v) sub- period 4: 15/09/2008-20/11/2008.

It should be noted that different VAR systems are estimated in respect to methods (i) and (iii) for the long period and also for each sub-period. It can also be noted that a consequence of this is that the estimated correlation can differ in respect to the stable period. This can be seen, for example, in Figure A4.1 in this chapter's appendix (Section 4.6).

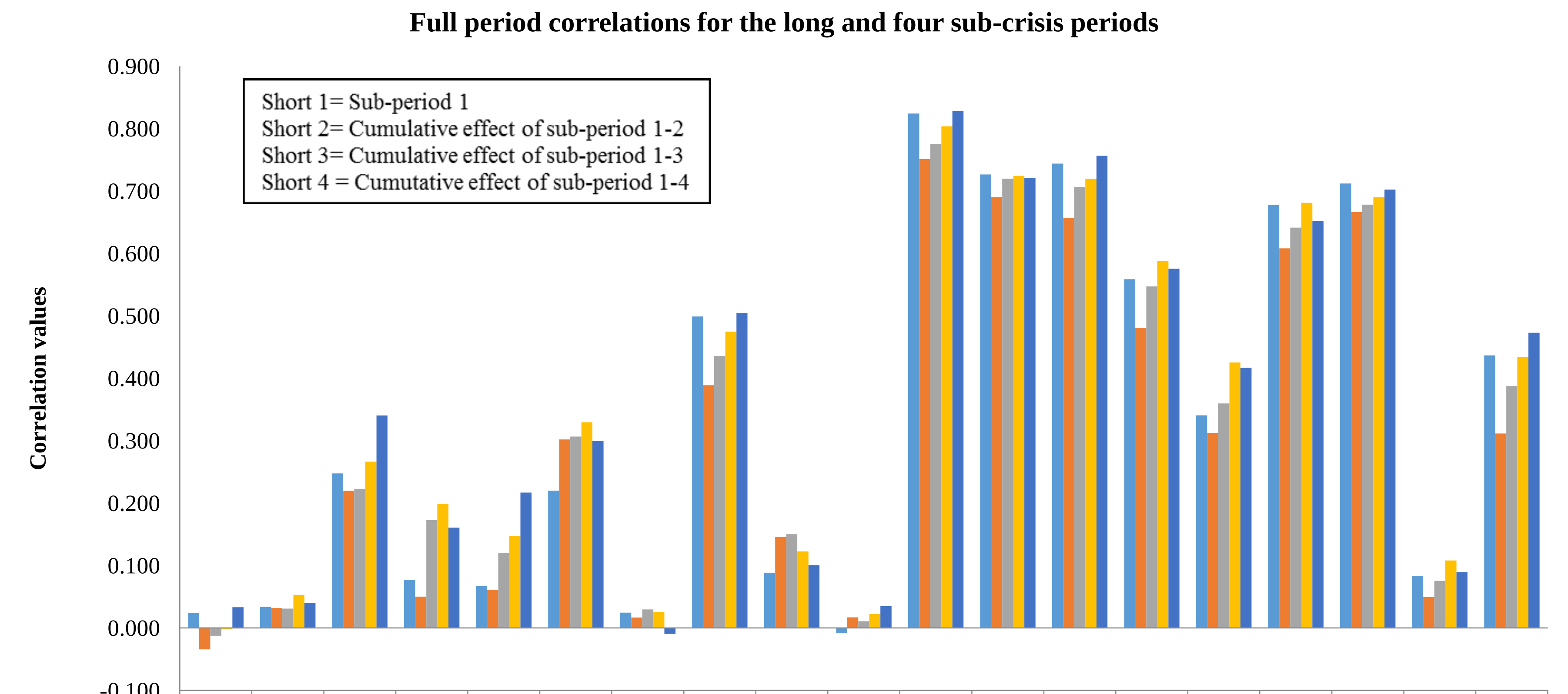
4.3.1.1 Correlations using the base case method

[23]Figure 4.1 below show the full period correlation (low volatility period) estimates based on the Forbes and Rigobon (2002) methodology for all sampled countries across all testing periods.

The pre-crisis *stable period*, the *crisis period* using the adjusted correlation (see equation 4.9 for the adjustment) and, for comparative purposes, the *unadjusted crisis period* correlations are presented in Figures A4.1 through to A4.3 in this chapter's appendix.

[23] Figures preceded by "A" are found in chapter appendices.

Figure 4.1: Full period correlations with US market (base case methodology covering various periods)



	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.024	0.034	0.248	0.077	0.067	0.220	0.025	0.499	0.089	-0.008	0.824	0.727	0.744	0.559	0.341	0.678	0.712	0.083	0.437
Short 1	-0.034	0.032	0.220	0.050	0.061	0.302	0.017	0.389	0.146	0.017	0.751	0.690	0.657	0.480	0.312	0.608	0.666	0.050	0.312
Short 2	-0.012	0.031	0.223	0.173	0.120	0.307	0.030	0.436	0.150	0.011	0.775	0.720	0.707	0.547	0.360	0.642	0.678	0.075	0.388
Short 3	-0.002	0.053	0.266	0.199	0.148	0.330	0.026	0.475	0.123	0.023	0.804	0.724	0.720	0.588	0.425	0.681	0.691	0.108	0.434
Short 4	0.033	0.040	0.340	0.161	0.217	0.299	-0.010	0.505	0.101	0.035	0.828	0.721	0.757	0.576	0.417	0.652	0.702	0.089	0.473

4.3.1.1.1 Stylised facts

It is clear from Figure 4.1 that across the full period each model runs, correlations with the US were a lot lower in respect to African markets than they were in respect to developed markets. Some differences in correlations can be observed in respect to the sub-periods over which the models were run. These were considerably smaller over the stable period, as shown in Figure A4.1, but more pronounced during the crisis period (unadjusted), as shown in Figure A4.3.

The long period model

During the stable period (Figure A4.1), Botswana, Côte d'Ivoire, Morocco, Nigeria and China have negative correlations with the US before the crisis. The result is surprising for Nigeria as it is considered one of Africa's most liquid markets. The smallest correlation value (−0.042) observed during the stable period is between Botswana and the US. While most African markets have correlations of less than 10%, South Africa's correlation is 35% (0.354).

With the exception of Japan, all the developed markets (Canada, France, Germany, Italy, Spain and UK) have correlations with the US higher than the African markets. All the developed markets, excluding Japan, have above 40% correlation with the US. South Africa is the only African market with correlation (0.354) higher than a developed market (Japan −0.276).

The adjusted crisis period correlations are shown in Figure A4.2. It can be observed that with the exception of Egypt, Namibia, Zambia, France and Japan, correlations are higher than their respective stable period correlations. Nigeria's adjusted correlation of 0.030 (3.0%) is the second smallest after Côte d'Ivoire's at 0.027 (2.7%) but they are higher than their respective stable period correlations of −0.017 and −0.042. This indicates that these markets in one way or the other have reacted to the financial crisis.

For comparative purposes, the unadjusted crisis period correlations are shown in Figure A4.3. It can be noted here that the introduction of a correction factor had the effect of reducing the estimated correlation values. The likely impact of this is that the correction factor reduces the likelihood of contagion being identified using the Forbes and Rigobon (2002) definition.

In summary, it can be noted that in the long period model:

- Botswana, Morocco and Nigeria are the only African countries with adjusted crisis period correlations higher than their full period correlations in the long crisis period;
- No developed country market have an adjusted crisis period correlation higher than their full period correlation in the long crisis sample;
- Unlike the majority of African markets examined, China (another emerging market) shows a significant increase in correlation in the crisis period.

Short period models

An examination of Figure A4.1 indicates that although the stable period correlations show some variations in respect to the different crisis time frame definitions, these differences are not pronounced. Greater differences are seen, however, in respect to the adjusted crisis period correlations in Figure A4.2.

Compared with the full period correlations (Figure 4.1 above), the crisis correlation in sub-period 1 is higher in Botswana, Morocco and Nigeria. Côte d'Ivoire provided no change while Egypt, Mauritius, Namibia, South Africa, Tunisia and Zambia had their full period correlations higher than their adjusted correlations in sub-period 1. China and India also have adjusted crisis correlations higher than the full period correlations. All developed markets' adjusted correlations of sub-period 1 are found to be smaller than the adjusted long crisis period correlations and also smaller than their respective full period correlations.

The result is very different for the cumulative impact of sub-period 1- 2. In fact, in Botswana, Morocco and Nigeria the adjusted crisis correlations went negative. Apart from Zambia, the sample period found no adjusted correlation higher than the full period correlation across all countries including the comparative markets (China and India).

For the cumulative effect of sub-period 1-3 (sub-period 3), Côte d'Ivoire, Mauritius, Morocco and Nigeria have their adjusted crisis period correlations higher than the full period. Again, no developed country market adjusted correlation is higher than the full period correlation in sub-period 1-3.

The cumulative effect of sub-period 1-4 produced a very different result from that of sub-period 1-3. This time, Nigeria's adjusted crisis correlation went negative from 0.055 in sub-period 1-3 to −0.041 in sub-period 1-4. China is the only market to have its adjusted crisis correlations higher than its full period correlation in the cumulative sub-period 1-4.

4.3.1.2 Correlations of the log returns based method

Using log returns from the daily closing values, raw correlations are calculated between the US and each comparator market. The results are provided in Figures A4.4 to A4.7 in the chapter appendix (Section 4.6).

Unlike with the VAR-system based models, correlation computation in this section does not require any regression estimation; therefore, the *stable period* correlations (see Figure A4.5 in appendix) remain constant in respect to the long period and sub-period models. Changes in correlation figures are, however, observed in the *crisis* and *full periods* given that these differ in length in the various sub-period models.

4.3.1.2.1 Stylised facts

The log returns model was undertaken for robustness and comparison purposes. If Figure A4.4 (full period correlations from log returns) is considered, it can be seen that correlations are generally a little higher than the base case model in Figure 4.1 above. However, the between-country differences are broadly similar. For example, African country correlations are generally much lower than those found in respect to developed markets. This preliminary examination of the data would suggest there is unlikely to be much difference in respect to contagion between the two models.

The long period model

Figure A4.5 indicates that in respect to the stable period, Botswana, Côte d'Ivoire, Morocco, Nigeria and Zambia have negative correlations. In terms of the developed markets, all correlations with the exception of Japan's are higher than African markets' correlations. This time, the UK has the highest correlation of 0.663 (66.3%) with the US, contrary to Figure A4.1 where the correlation in respect to Canada was marginally higher. Overall, however, there were only limited differences between the two correlations in respect to the two methodologies.

The adjusted correlations in respect to the crisis period, shown in Figure A4.6, are higher than the stable period correlations in all African markets. In the developed markets, the adjusted crisis correlations are also higher in most countries except in Italy and the UK.

Botswana, Morocco and China have adjusted crisis period correlations higher than their full period correlations (Figures A4.4 and A4.6). Although Zambia produced a negative correlation (−0.004) in the adjusted crisis period, it is found to be higher than the full period correlation (−0.007).

The highest full period correlation is observed in Canada (0.803). France, Germany, Spain and the UK also have relatively huge correlations with the US during the full period (Figure A4.4). However, when compared to the adjusted crisis correlations, no developed market produced an adjusted correlation higher than the full period correlation. For the comparative markets, China's adjusted correlation of 0.188 is higher than its full period correlation of 0.155. Relative to the stable period, all full period correlations are higher in all countries except Namibia.

If the values found in Figure A4.6 are compared with those in Figure A4.2, it can be identified that there is a similar pattern as found in respect to the full period data. Specifically, that although the correlation in the log returns data are higher, there is a very similar pattern in terms of the relative correlations of African and developed markets.

Short period models

If sub-period 1 and all the cumulative sub-period models are considered in Figure A4.5, essentially the same patterns are observed. Negative correlations are observed in Botswana (−0.014), Côte d'Ivoire (−0.054), Morocco (−0.027), Nigeria (−0.040) and Zambia (−0.015) throughout the four sub-crisis and the long crisis periods. The highest correlation for the African market is observed in South Africa (0.425).

France provided the highest stable period correlation with the US at a value of 0.660, while Japan gave the lowest developed market correlation during the stable period. For the comparative markets, China's correlation is 0.036 while India's is 0.266. Overall minimum correlation is observed in Morocco.

If the unadjusted crisis period model (Figure A4.7) is compared with the adjusted crisis period model (Figure A4.6), it can be identified that after adjusting for heteroscedasticity in line with Forbes and Rigobon (2002), all the crisis period correlations across all countries decreased. The highest adjusted correlation observed in the African market for sub-period 1 is between the US and Egypt at a value of 0.241 while the lowest is 0.017, found between the US and Nigeria. South Africa produced the highest adjusted correlation for the cumulative sub-periods 1- 2 (0.265), 1-3 (0.272) and 1-4 (0.325), while Zambia's correlations of −0.043 and 0.0015 are the lowest in cumulative sub-periods 1-2, and 1-3. The lowest correlation observed in the African markets for sub-period 1-4 is between the US and Nigeria at a value of −0.059.

For the developed market, the highest adjusted correlation is observed in Germany for sub-period 1 (0.565) and sub-period 1-4 (0.583) and in Canada for sub-period 1-2 (0.506) and 1-3 (0.548). Japan produced the lowest correlation in sub-periods 1 and 1-4, while Italy's correlations are the lowest in sub-periods 1-2 and 1-3. The overall highest sub-crisis correlation is observed in Canada (0.575) in sub-period 1-4. For the comparative markets, India's correlation is higher than China's throughout the sub-crisis periods, including the long crisis period.

When compared to the full period correlations, the adjusted crisis correlations for Botswana, Cote d'Ivoire, Mauritius and Morocco are higher in sub-period 1. The remaining African markets' full correlations are higher than the adjusted correlation with South Africa producing the highest full period correlation value (0.474). For the cumulative impact of sub-periods 1-2, and 1-3, adjusted correlations are higher than the full period correlations in Botswana, Côte d'Ivoire, Morocco and Nigeria. The lowest full period correlations observed in sub-periods 1-2, and 1-3 are between Zambia and the US. The adjusted correlation of Côte d'Ivoire of −0.024 for the sub-period 1-4 decreased significantly below its full period correlation. Morocco's adjusted correlation for sub-period 1-4 is the only African correlation value higher than its full period correlation.

For the developed markets, all the full period correlations are higher than the adjusted correlations across all sub-periods. The highest full period correlation is found in Canada across all sub-periods. Japan provided the lowest full period correlations from sub-period 1 through to 4.

To summarise, it can be identified that:

1. Reduction in unadjusted correlations after the first crisis period is consistent in Botswana, Tunisia and India throughout the sub-periods;
2. Adjusted correlations in Botswana, Côte d'Ivoire and Morocco are higher than their full period correlations in sub period 1, sub-periods 1-2 and 1-3. Mauritius, Namibia and Zambia's adjusted correlations are higher than their full period correlations in sub-period 1, while the adjusted correlations in Nigeria are higher than the full period correlations in sub-periods 1-2 and 1-3;

3. Egypt, Namibia, South Africa and Tunisia's adjusted correlations are lower than their full period correlations across all sub-periods;
4. All the developed markets' full period correlations are higher than their respective adjusted correlations across all sub-periods;
5. China and India's adjusted correlations are higher than their full period correlations in sub-period 1. China's adjusted correlations also remain higher than the full period correlations in the remaining periods.

4.3.1.3 Correlations of the two separate VAR systems method

Figures A4.8-A4.10 in the chapter appendix show correlation estimates based on two separate VAR systems in respect to the cumulative impact of sub-period 1-4 and the long crisis period. Sub-periods 1, 1-2 and 1-3 cannot be tested because of their relatively small sample sizes. The figures show, respectively, the *full period*, the *stable period* and the *crisis period*.

4.3.1.3.1 Stylised facts

If the full period correlations of the separate VAR model (Figure A4.8), are compared with the base case model in Figure 4.1 above we see that the results are identical. This reflects the fact that the full period model is based on a single VAR system in both cases.

From Figure A4.9 it can be identified that Botswana, Morocco, Nigeria and China have negative correlations in the stable period before the crisis. Canada produced the highest correlation with the US while South Africa (0.382) is the only African market to have correlation higher than a developed market – Japan (0.276). It can also be noted that the values are identical for the long period and for the cumulative impact of sub-period 1-4, which reflects the fact that the same stable period VAR system is used for both.

The long period model

In the long crisis period (Figure A4.10), Botswana's correlation increased to 0.051, Morocco's increased to 0.083, Nigeria's increased to 0.044 and China's increased to 0.142. These markets produced negative correlations in the stable period. The changes found in them are set to be substantial due to the low level of correlations that existed before the crisis.

While most correlations increased during crisis, some reductions are observed in Namibia and Zambia during the long crisis period. South Africa is the only African market with high correlation with the US, at a value of 0.577. All the developed country markets correlations increased during the crisis. Canada produced the highest correlation value with the US at 0.863. Germany, Italy, Spain and the UK have correlations above 50%. Japan is the only developed market with a less than 40% correlation with the US, producing a value of 37% (0.374) during the crisis period. The major findings of the separate VAR long period correlations can be summarised as:

- Except for Namibia and Zambia, all the crisis period correlations are higher than the stable period correlations in African markets;
- All developed country markets' correlations are also higher during the crisis period when compared with the stable period correlations;
- The highest correlation during the crisis period is found in Canada for the developed markets and South Africa for the African markets, but Canada has the overall highest correlation.

If these values are compared with the adjusted single VAR model results in Figure A4.2, correlations are generally higher, for example, for Egypt 0.297 compared with 0.210, and for

Canada 0.864 compared with 0.776. This gives an indication that contagion is more likely to be found given that the stable period correlation values are identical for both models.

Short period model

The correlation results obtained from the separate VAR analysis for the cumulative impact of sub-period 1-4 are depicted in appendix Figure A4.10 for the crisis period. The results show that correlations are higher during the crisis when compared with the stable period or the long crisis period. For instance, the correlation in Botswana is −0.038 during the stable period, which increased to 0.104 during the crisis. Morocco's correlation also increased from −0.043 during stability to 0.486 during the crisis. Namibia's correlation is higher during the crisis period when compared with the stable period and even the long crisis period.

Côte d'Ivoire and Nigeria did particularly badly during the crisis. Côte d'Ivoire's correlation with the US during the crisis period stands at −0.094, while Nigeria's stands at −0.281. The highest African market correlation during the crisis is produced between South Africa and the US at a value of 0.716. For the developed markets, all correlations during the crisis are found to be higher than the correlations during stability. Not only that, they are also higher than the crisis correlations of the long period. China's crisis correlation also shows a substantial increase from the stable period correlation. The correlation increased from −0.001 during stability to 0.311 during the crisis. If these values are compared with the sub-periods adjusted single VAR model results in Figure A4.2, correlations are generally higher. For example, for Egypt 0.645 compared with 0.227 and for Canada 0.910 compared with 0.609. This also gives an indication that contagion is more likely to be found given that the stable period correlation values are identical for both models.

The tests for contagion will now be presented in the next section to identify whether or not this is in fact the case.

4.4 RESULTS PART 2: CONTAGION TESTING

The following hypotheses are tested in respect to each of the three correlation contagion models identified in Section 4.1:

Hypothesis 1

Hypothesis 1a: There is a statistically significant increase in correlations between US and developed markets over the period 15 September 2008-15 October 2009.

Hypothesis 1b: There is a statistically significant increase in correlations between US and African markets over the period 15 September 2008-15 October 2009.

Hypothesis 2

Hypothesis 2a: There is a statistically significant increase in correlations between US and developed markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

Hypothesis 2b: There is a statistically significant increase in correlations between US and African markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

These hypotheses are tested by means of testing the significance of a test statistic (see equation 4.12). The null of market *interdependence* is tested against the alternative of *contagion* through the following hypothesis test:

$$H_0 : \rho_a^h \leq \rho^l \quad (4.18)$$

$$H_A : \rho_a^h > \rho^l \quad (4.19)$$

$where\ \rho_a^h$, is the correlation during the high volatility period, and ρ^l, is the correlation during the low volatility period. The hypothesis above is applied to the Forbes and Rigobon (2002) base case method and the raw log returns model.

For the separate VARs model, the hypothesis is estimated as:

$$H_0 : \rho^c \leq \rho^s \quad (4.20)$$

$$H_A : \rho^c > \rho^s \quad (4.21)$$

$where\ \rho^c\ and\ \rho^s$ are correlations of crisis and stable periods.

4.4.1 Single VAR system contagion test results

The following provides a summary of the correlation in the stable, crisis (high volatility period) and full (low volatility period) periods along with their respective standard deviations. The test is undertaken in respect to the difference between the *low volatility period* and *high period* correlations. The test statistic follows a t-distribution, with contagion identified as occurring if the null hypothesis has a one-tail 5% or less probability value. In large samples, the t-value will need to be greater than or equal to 1.645.

Long period contagion tests

Tables 4.2A and 4.2B present the result for the long period models.

Table 4.2A: Hypothesis 1 (single VAR long period unadjusted correlation contagion test)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.042	0.003	0.091	0.002	0.024	0.003	0.913	NO
Côte d'Ivoire	-0.009	0.009	0.038	0.164	0.034	0.103	0.063	NO
Egypt	0.248	0.008	0.294	0.015	0.248	0.011	0.594	NO
Mauritius	0.045	0.005	0.095	0.008	0.077	0.006	0.251	NO
Morocco	-0.020	0.005	0.118	0.006	0.067	0.005	0.701	NO
Namibia	0.259	0.010	0.209	0.022	0.220	0.016	-0.163	NO
Nigeria	-0.017	0.004	0.042	0.007	0.025	0.005	0.233	NO
South Africa	0.354	0.007	0.573	0.011	0.499	0.009	1.431*	NO
Tunisia	0.063	0.003	0.106	0.004	0.089	0.003	0.246	NO
Zambia	0.003	0.006	-0.016	0.007	-0.008	0.007	-0.111	NO
Developed markets								
Canada	0.689	0.006	0.864	0.013	0.824	0.010	**1.934****	**YES**
France	0.649	0.007	0.761	0.012	0.727	0.009	1.081	NO
Germany	0.583	0.006	0.800	0.013	0.744	0.010	**1.916****	**YES**
Italy	0.442	0.004	0.599	0.009	0.559	0.007	0.827	NO
Japan	0.276	0.011	0.374	0.007	0.341	0.009	0.513	NO
Spain	0.561	0.007	0.730	0.012	0.678	0.009	1.436*	NO
United Kingdom	0.628	0.006	0.753	0.011	0.712	0.008	1.214	NO
Other markets								
China	-0.002	0.013	0.165	0.012	0.083	0.013	1.112	NO
India	0.189	0.010	0.559	0.015	0.437	0.012	**2.215****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table 4.2B: Hypothesis 1 (single VAR long period adjusted correlation contagion test)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion[24]
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.042	0.003	0.066	0.002	0.024	0.003	0.562	NO
Côte d'Ivoire	-0.009	0.009	0.027	0.164	0.034	0.103	-0.088	NO
Egypt	0.248	0.008	0.210	0.015	0.248	0.011	-0.468	NO
Mauritius	0.045	0.005	0.069	0.008	0.077	0.006	-0.111	NO
Morocco	-0.020	0.005	0.084	0.006	0.067	0.005	0.237	NO
Namibia	0.259	0.010	0.151	0.022	0.220	0.016	-0.984	NO
Nigeria	-0.017	0.004	0.030	0.007	0.025	0.005	0.075	NO
South Africa	0.354	0.007	0.449	0.011	0.499	0.009	-0.885	NO
Tunisia	0.063	0.003	0.078	0.004	0.089	0.003	-0.152	NO
Zambia	0.003	0.006	-0.011	0.007	-0.008	0.007	-0.048	NO
Developed markets								
Canada	0.689	0.006	0.776	0.013	0.824	0.010	-1.871	NO
France	0.649	0.007	0.646	0.012	0.727	0.009	-2.132	NO
Germany	0.583	0.006	0.690	0.013	0.744	0.010	-1.550	NO
Italy	0.442	0.004	0.473	0.009	0.559	0.007	-1.194	NO
Japan	0.276	0.011	0.275	0.007	0.341	0.009	-0.973	NO
Spain	0.561	0.007	0.610	0.012	0.678	0.009	-1.602	NO
United Kingdom	0.628	0.006	0.636	0.011	0.712	0.008	-1.947	NO
Other markets								
China	-0.002	0.013	0.119	0.012	0.083	0.013	0.478	NO
India	0.189	0.010	0.431	0.015	0.437	0.012	-0.094	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Stylised facts in respect to long period tests

In respect to the Hypothesis 1 based results, the first thing to note is that while none of the tests undertaken in respect to the adjusted correlation coefficient (Table 4.2B) show contagion, a number of the tests do for the unadjusted correlations. This is constant with the findings of Forbes and Rigobon (2002), who found no contagion in emerging markets after adjusting for heteroscedasticity during the 1987 stock market crash, 1994 Mexican peso crisis and the 1997 Asian crisis.

[24] The tables report the unadjusted (conditional) and adjusted (unconditional) correlations tests. The test statistics is for one-sided t-test at a 5% significant level. A yes in the last column indicates contagion while a no indicates the lack of contagion in the markets.

If we want to compare African and developed markets it is necessary to focus on the unadjusted correlation-based tests. It can be noted that while there is no contagion in African markets in the unadjusted test, South Africa has a high test statistic of 1.431. Contagion effects were found in respect to the developed markets Canada and Germany, and the emerging market of India. The remaining developed markets and China indicated no contagion effect.

It can be noted that there is evidence of what Forbes and Rigobon (2002) define as interdependence. They identify this as crisis period increases in correlation that occur between countries that show high stable period correlations (defined as 40% or more in this thesis). This is evident in the correlations levels between the US and France, Italy, Spain and the UK before the crisis.

Other interesting features can be identified in the data. For example, Japan produced the lowest test statistic of 0.513 for the developed markets while Namibia has the lowest test statistics (−0.163) across all markets. While the result of no contagion in South Africa is surprising, the higher level of correlation in comparison with the remaining African markets obtained is expected, as the South African stock market is the largest in Africa. Also, if the restriction on the significance level was relaxed to, say, 10%, South Africa’s and Spain’s test statistics (1.431 and 1.436, respectively) could have provided evidence of contagion.

Lack of contagion in all African markets and most developed markets is shocking by the fact that the crisis tested is considered by experts as the worst financial crash since the Great Depression of 1929.

Short sub-period contagion tests

The short sub-period tests presented below relate to Hypothesis 2 and cover the respective sub-periods; 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008. The findings are presented in the chapter appendix (Section 4.6) in Tables A4.1a, A4.2a, A4.3a and A4.4a for the unadjusted tests. The adjusted tests are presented in Tables A4.1b, A4.2b, A4.3b and A4.4b also in the chapter appendix.

Stylised facts in respect to short sub-period tests

The pattern in respect to the differences found using the adjusted and unadjusted (conditional) correlation measures is very similar to the findings in respect to Hypothesis 1. Specifically, while no evidence of contagion is found in relation to the adjusted measure, contagion is found using the unadjusted measure. From the unadjusted (conditional) tests, the results show evidence of contagion in:

1. Germany, China and India in sub-period 1 (Table A4.1a);
2. Canada, Germany, China and India in respect to the cumulative impact of sub-period 1-2 (Table A4.2a);
3. Mauritius, Canada, Germany, Spain, China and India in respect to the cumulative impact of sub-period 1-3 (Table A4.3a);
4. Morocco, South Africa, Canada, Germany and India in respect to the cumulative impact of sub-period 1-4 (Table A4.4a).

The findings tend to be consistent among African markets in sub-periods 1 and 2 where no contagion is found in respect to the conditional measure. Mauritius became contaminated in sub-period 1-3. And for the cumulative impact of sub-period 1-4, Morocco and South Africa are the only contaminated African markets.

If you look at the linkages between African and US markets across the four sub-periods, it is evident that these markets are not highly connected. Given that stable period correlations are low, it can be concluded that neither contagion nor interdependence effects are present in Africa. *It can be speculated that any impact on African markets could be a spill-over effect derived from linkages that exist across the region. South Africa can be considered the potential channel of such effects because it has the highest correlation with the US among the African markets.*

As regards the developed markets, there is consistent evidence of Germany being contaminated throughout the four sub-crisis periods. Canada is found to be contaminated in sub-periods 1-2, 1-3 and 1- 4. Spain became contaminated in sub-period 1-3. However, it is worth noting that high correlation between the developed markets and the US where contagion is not found is very evident. It is possible to speculate that these countries could be affected by interdependence effects at different sub-crisis stages, or spill-over derived from, say, Germany which is contaminated. These effects are obviously not being detected here, as I did not test for spill-over effect.

4.4.2 Log returns contagion test results

The testing of Hypothesis 1 and Hypothesis 2 is repeated in this section using the correlation estimates derived from the log returns based methodology. This model is implemented in order to obtain results that allow direct comparison with the single VAR approach before and after adjusting for heteroscedasticity. In line with Forbes and Rigobon (2002), I am more concern with the results obtained after adjusting the crisis correlation for heteroscedasticity. If the results derived from using the two different methodologies are similar, I will be able to conclude that the results are relatively robust using both approaches.

Long period contagion tests

Table 4.3A: Hypothesis 1 (log returns long period unadjusted correlation contagion test)

African markets	**Stable period**		**Crisis period**		**Full period**		**Test statistics**	**Evidence of contagion?**
	ρ	**σ**	**ρ**	**σ**	**ρ**	**σ**		
Botswana	-0.014	0.005	0.102	0.004	0.046	0.004	0.757	NO
Côte d'Ivoire	-0.054	0.006	0.018	0.201	0.015	0.126	0.041	NO
Egypt	0.131	0.011	0.383	0.021	0.316	0.016	0.910	NO
Mauritius	0.009	0.008	0.163	0.013	0.117	0.010	0.655	NO
Morocco	-0.027	0.007	0.168	0.010	0.102	0.008	0.917	NO
Namibia	0.341	0.013	0.274	0.029	0.289	0.021	-0.222	NO
Nigeria	-0.040	0.009	-0.007	0.016	-0.015	0.012	0.102	NO
South Africa	0.425	0.010	0.624	0.017	0.562	0.013	1.327*	NO
Tunisia	0.126	0.005	0.223	0.005	0.178	0.005	0.645	NO
Zambia	-0.015	0.008	-0.006	0.009	-0.007	0.008	0.022	NO
Developed markets								
Canada	0.653	0.007	0.846	0.018	0.803	0.012	**1.850****	**YES**
France	0.660	0.009	0.793	0.018	0.758	0.013	1.246	NO
Germany	0.594	0.009	0.827	0.018	0.770	0.013	**2.200****	**YES**
Italy	0.484	0.007	0.596	0.016	0.571	0.012	0.533	NO
Japan	0.378	0.010	0.515	0.017	0.470	0.013	0.805	NO
Spain	0.578	0.009	0.750	0.017	0.704	0.013	1.373*	NO
United Kingdom	0.663	0.008	0.780	0.016	0.746	0.012	1.118	NO
Other markets								
China	0.036	0.018	0.265	0.017	0.155	0.017	1.551*	NO
India	0.266	0.014	0.587	0.021	0.476	0.017	**2.095****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table 4.3B: Hypothesis 1 (log returns long period adjusted correlation contagion test)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.014	0.005	0.099	0.004	0.046	0.004	0.712	NO
Côte d'Ivoire	-0.054	0.006	0.013	0.201	0.015	0.126	-0.030	NO
Egypt	0.131	0.011	0.277	0.021	0.316	0.016	-0.513	NO
Mauritius	0.009	0.008	0.116	0.013	0.117	0.010	-0.007	NO
Morocco	-0.027	0.007	0.119	0.010	0.102	0.008	0.231	NO
Namibia	0.341	0.013	0.197	0.029	0.289	0.021	-1.345	NO
Nigeria	-0.040	0.009	-0.005	0.016	-0.015	0.012	0.130	NO
South Africa	0.425	0.010	0.491	0.017	0.562	0.013	-1.340	NO
Tunisia	0.126	0.005	0.160	0.005	0.178	0.005	-0.248	NO
Zambia	-0.015	0.008	-0.004	0.009	-0.007	0.008	0.045	NO
Developed markets								
Canada	0.653	0.007	0.748	0.018	0.803	0.012	-1.931	NO
France	0.660	0.009	0.678	0.018	0.758	0.013	-2.315	NO
Germany	0.594	0.009	0.725	0.018	0.770	0.013	-1.415	NO
Italy	0.484	0.007	0.464	0.016	0.571	0.012	-2.022	NO
Japan	0.378	0.010	0.391	0.017	0.470	0.013	-1.313	NO
Spain	0.578	0.009	0.625	0.017	0.704	0.013	-1.963	NO
United Kingdom	0.663	0.008	0.661	0.016	0.746	0.012	-2.348	NO
Other markets								
China	0.036	0.018	0.188	0.017	0.155	0.017	0.462	NO
India	0.266	0.014	0.453	0.021	0.476	0.017	-0.396	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Stylised facts in respect to long period tests

In respect to the Hypothesis 1 based results, the first thing to note is that while none of the tests undertaken in respect to the adjusted correlation coefficient (Table 4.3B) show contagion, a number of the tests in respect to the unadjusted correlations did (Table 4.3A). This is constant with the findings in respect to the single VAR system approach.

The unadjusted correlation tests presented in Table 4.3A also give similar results, in terms of the evidence of contagion, with the unadjusted single VAR test in Table 4.2A above. In particular it can be noted that no contagion is found in Africa.

Test statistics of 1.850, 2.200 and 2.095 indicate contagion effects in Canada, Germany and India. The highest overall statistic is from Germany, while −0.222 produced by Namibia is the lowest across all markets.

The result also indicates that China has high test statistics of 1.551, which is insignificant at the 5% significant level. If I relax the significance restriction, this market would have been significant at, say, 10%.

The analysis of correlations from this approach reflects that with the exception of Japan, the rest of the developed markets are highly correlated with the US. This suggests that an interdependence effect has occurred in these markets during the crisis. This is found where high correlations increased during the crisis as evident across all the developed markets (Table 4.3A).

Short period contagion tests

The short sub-period tests presented in Tables A4.5a to A4.8b in the chapter appendix relate to Hypothesis 2 and cover the respective sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008. Tables A4.5a, A4.6a, A4.7a and A4.8a are for the unadjusted tests. The adjusted tests are presented in Tables A4.5b, A4.6b, A4.7b and A4.8b.

Stylised facts in respect to short sub-period tests

The Hypothesis 2 results obtained for sub-period 1 in this section are similar to the results obtained in sub-period 1 based on a single VAR in Table A4.1a. Differences are observed in the value of the test statistics obtained. But for the cumulative impact sub-periods 1-2, 1-3 and

1-4, there are differences in the countries contaminated during the crisis compared with the ones observed in Section 4.4.1. The unadjusted log returns tests show contagion in:

- Germany, China and India (Table A4.5a) as in the single VAR test for sub-period 1 (Table A4.1a);
- Morocco and India in respect to the cumulative impact of sub-period 1-2 (Table A4.6a);
- Morocco and China in respect to the cumulative impact of sub-period 1- 3 (Table A4.7a);
- Morocco, Germany and India in respect to the cumulative impact of sub-period 1-4 (Table A4.8a).

Surprisingly, Germany is only contaminated in sub periods 1 and 1-4, unlike the single VAR model where contagion consistency is found in Germany throughout all sub-periods. Another difference that is worth noting is that Morocco was contaminated from the cumulative impact of sub-periods 1-2, 1-3 and 1-4 while, in the single VAR approach, Morocco's contamination is only evident on the impact of sub-period 1-4. It is also found that India is not contaminated from the cumulative impact of sub period 1-3 in this section, unlike the single VAR approach where India is contaminated in sub-period 1 and all the cumulative sub-periods.

It can also be noted that there are a number of t-test values marginally below the contagion threshold of 1.645. For example, the t values of 1.621 and 1.494 were found in Botswana and France in sub-period 1 (Table A4.5a). The result is surprising for Botswana as sub-period 1 had very low correlations during the stable and full periods (-0.014 and -0.011) although this increased to 0.392 during crisis. This finding may be indicative of herding behaviour.

For the cumulative impact of sub-period 1-2 (Table A4.6a), Mauritius, Germany and China also produced high but insignificant statistics of 1.488, 1.481 and 1.577. Mauritius and Germany subsequently produced insignificant t-statistics on the cumulative impact of sub-period 1-3 (Table A4.7a) at 1.630 and 1.543. Another high t-statistic is observed in India at 1.422 in sub-period 1-3 and increased further in sub-period 1-4 to 2.076 to suggest evidence of contagion.

When the adjusted correlation data is considered it can be noted that all evidence of contagion found in both African and developed country markets disappeared across all four sub-crisis periods.

The findings of the adjusted contagion test based on raw log returns across all samples are in line with Forbes and Rigobon (2002:2236), who reported: *"Changing the model specification has no significant impact on results. For example, using daily or weekly returns, local currency returns, greater or fewer lags, and/or varying the interest rate controls, does not change our central findings. Moreover, the sensitivity analysis also shows that focusing only on the cross-market correlation coefficient with daily returns, no lags, and no interest rate controls actually strengthens our central results"*.

4.4.3 Separate VAR systems contagion test results

The testing of Hypothesis 1 and Hypothesis 2 is repeated in this section using the correlation estimates derived from two separate VAR systems. This model is implemented in order to obtain results that allow direct comparison with the results from the alternative approaches presented in Sections 4.4.1 and 4.4.2.

Long period and sub-period 1-4 contagion tests

Table 4.4: Hypothesis 1 (separate VAR systems long period contagion test)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.038	0.003	0.051	0.002	0.024	0.003	1.096	NO
Côte d'Ivoire	0.024	0.005	0.039	0.173	0.034	0.103	0.191	NO
Egypt	0.100	0.008	0.297	0.014	0.248	0.011	**2.232****	**YES**
Mauritius	0.035	0.005	0.096	0.008	0.077	0.006	0.768	NO
Morocco	-0.043	0.005	0.083	0.006	0.067	0.005	1.566*	NO
Namibia	0.298	0.009	0.211	0.023	0.220	0.016	-1.171	NO
Nigeria	-0.015	0.004	0.044	0.007	0.025	0.005	0.727	NO
South Africa	0.382	0.007	0.577	0.011	0.499	0.009	**3.203*****	**YES**
Tunisia	0.077	0.003	0.121	0.004	0.089	0.003	0.550	NO
Zambia	0.007	0.006	-0.012	0.007	-0.008	0.007	-0.236	NO
Developed markets								
Canada	0.680	0.006	0.863	0.013	0.824	0.010	**5.959*****	**YES**
France	0.653	0.006	0.763	0.012	0.727	0.009	**2.804*****	**YES**
Germany	0.587	0.006	0.799	0.013	0.744	0.010	**5.354*****	**YES**
Italy	0.457	0.004	0.597	0.009	0.559	0.007	**2.464*****	**YES**
Japan	0.276	0.007	0.374	0.011	0.341	0.009	1.343*	NO
Spain	0.563	0.007	0.728	0.011	0.678	0.009	**3.628*****	**YES**
United Kingdom	0.630	0.006	0.756	0.010	0.712	0.008	**3.085*****	**YES**
Other markets								
China	-0.001	0.013	0.142	0.012	0.083	0.013	**1.755****	**YES**
India	0.210	0.010	0.555	0.015	0.437	0.012	**5.095*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table 4.5: Hypothesis 2 (Cumulative separate VAR systems contagion test on sub-period 1-4

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.038	0.003	0.104	0.002	0.033	0.003	0.821	NO
Côte d'Ivoire	0.024	0.005	-0.094	0.004	0.040	0.005	-0.682	NO
Egypt	0.100	0.008	0.645	0.015	0.340	0.009	**3.211*** **	**YES**
Mauritius	0.035	0.005	0.288	0.009	0.161	0.006	1.525*	NO
Morocco	-0.043	0.005	0.486	0.006	0.217	0.005	**3.258*** **	**YES**
Namibia	0.298	0.009	0.320	0.014	0.299	0.010	0.140	NO
Nigeria	-0.015	0.004	-0.281	0.004	-0.010	0.004	-1.530	NO
South Africa	0.382	0.007	0.716	0.016	0.505	0.009	**2.937*** **	**YES**
Tunisia	0.077	0.003	0.206	0.007	0.101	0.004	0.756	NO
Zambia	0.007	0.006	0.153	0.004	0.035	0.006	0.835	NO
Developed markets								
Canada	0.680	0.006	0.910	0.021	0.828	0.009	**4.123*** **	**YES**
France	0.653	0.006	0.772	0.014	0.721	0.008	1.459*	NO
Germany	0.587	0.006	0.887	0.020	0.757	0.009	**4.372*** **	**YES**
Italy	0.457	0.004	0.697	0.013	0.576	0.006	**2.196** **	**YES**
Japan	0.276	0.007	0.555	0.021	0.417	0.009	**1.940** **	**YES**
Spain	0.563	0.007	0.756	0.015	0.652	0.008	**2.091** **	**YES**
United Kingdom	0.630	0.006	0.789	0.014	0.702	0.008	**1.945** **	**YES**
Other markets								
China	-0.001	0.013	0.311	0.013	0.089	0.012	**1.776** **	**YES**
India	0.210	0.010	0.717	0.022	0.473	0.011	**3.902*** **	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Stylised facts in respect to long period and cumulative sub-period 1-4

The estimated results for the Hypothesis 1 contagion effects using separate VARs are depicted in Table 4.4 above for the long crisis period. The nearest comparators are the results for the single VAR system based on adjusted results in Table 4.2B above.[25] There are considerable differences in the results in these two tables. Table 4.4 shows that contagion occurred frequently. The adjusted tests from the single VAR and log returns models above show no contagion. In African markets, Egypt and South Africa show contagion with t-test statistics of 2.232 and 3.203, respectively. There was also a high, but insignificant, t-statistic value of 1.566 in Morocco. All the developed markets except Japan showed evidence of

[25] Where adjustments to correlation estimates were made to control for higher volatility in the crisis period. Such adjustments are not required in a two VAR system to ensure comparability between correlation estimates.

contagion effect. Although Japan appears uncontaminated, it has a relative high statistics of 1.343. The two comparative emerging markets, China and India, also show evidence of contagion.

Data limitations meant that the short period contagion tests could only be undertaken for the cumulative impact of sub-period 1-4. Table 4.5 identifies that contagion is found in Egypt, Morocco and South Africa and all the developed country markets except France in this period (although high, but insignificant, statistics were produced: France-1.459 and Mauritius-1.525). The two emerging markets included for comparative purposes also showed evidence of contagion. The strongest contagion effect is found in Germany across all markets with a t-statistics value of 4.372. For the African markets, Morocco produced the strongest contagion effect at a t-value of 3.258.

4.5 MODEL COMPARISONS: SOME THOUGHTS AND CONCLUSIONS

While there is no much difference in respect to results between the single VAR and the log returns methodologies, the separate VAR system results suggest that evidence of contagion is significantly greater. Why is this? And which methodology is the more credible?

Comparisons can be made between the stable period and crisis period correlation estimates using the adjusted single VAR system (Table 4.2A) and the separate VAR system (Table 4.4). It can be noted that the stable period estimates are marginally lower and this may reflect an *element of bias* in the estimation procedure given that the low volatility (stable) period values are estimated for the VAR parameters obtained from the full period data: data that also incorporate the impact of the crisis on the estimated model. It is possible that the use of a single model in the estimation procedure, along with the adjustment made to control for heteroscedasticity bias in the variance, may mean that there are flaws in the Forbes and Rigobon (2002) model.

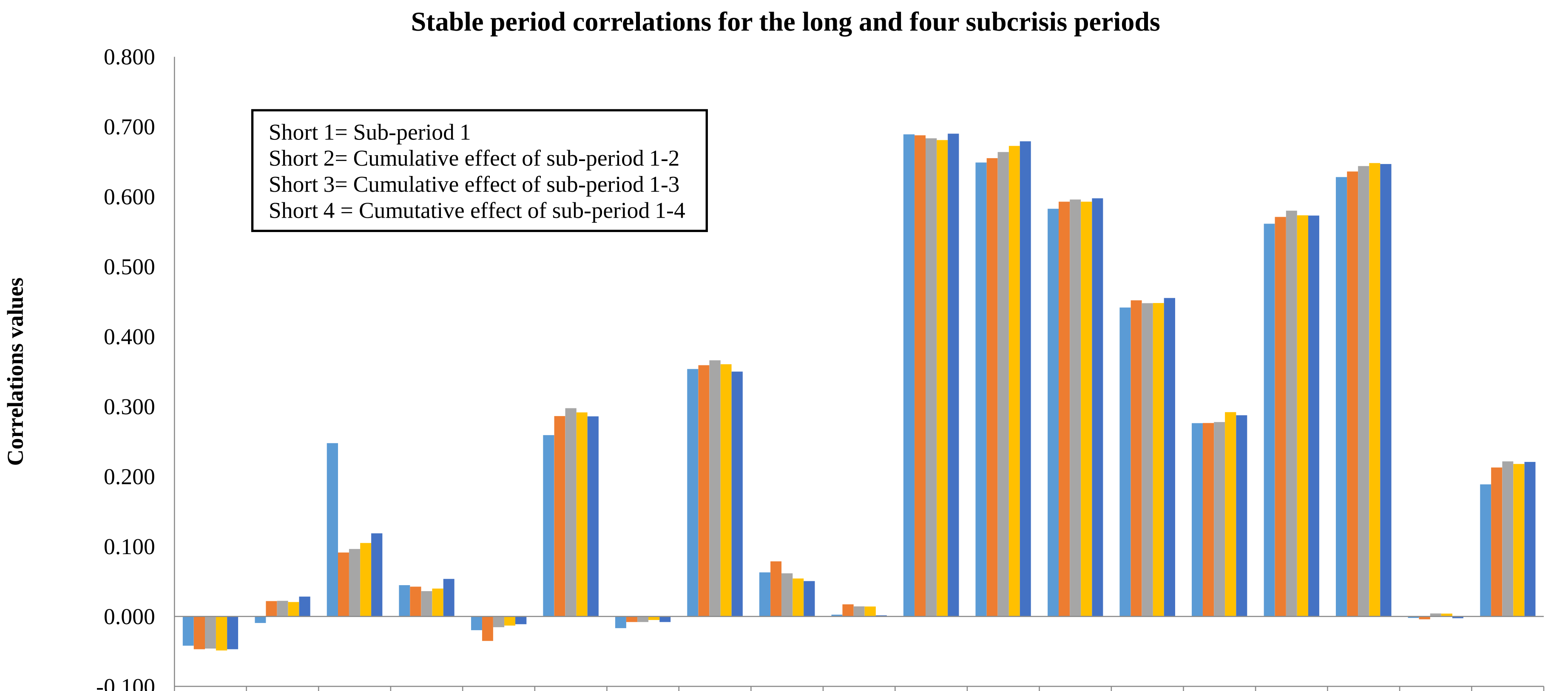
A number of peer-reviewed journal articles also identified issues with the Forbes and Rigobon (2002) approach. For instance, Dungey and Zhumabekova (2001) argue that the Forbes and Rigobon (1999, now 2002) results consistently over-reject the hypothesis of contagion largely because they compare a large sample of non-crisis period data with a small sample of crisis period data. Dungey and Zhumabekova (2001) also argued that the Forbes and Rigobon (2002) tests have very low power given that the ability to reject the null hypothesis can be affected by the sample size (2000: 1 and 4).

I would argue that of the three methodologies tested in this chapter, the separate VAR system approach produces the most credible estimates of contagion. It is not, however, without drawbacks. The principal ones being (i) it cannot be applied unless the crisis extends over a relative long period and (ii) it is based on a single point measure of correlation and therefore tells us nothing about how correlation (and therefore contagion) develops over time. It may very well be that in order to extend our understanding of contagion we need to incorporate time-varying correlation estimates into our analysis and this is what I will do in the next chapter, where I explore the issues identified in this chapter by using a multivariate DCC-GARCH based analysis.

The results from this chapter indicate that there was strong evidence that the 2007-09 financial crisis resulted in contagion from the US to most Western developed markets, but that the spread of contagion to African markets was limited to a few countries. I will examine whether or not this conclusion is supported using a multivariate DCC-GARCH based approach in the next chapter.

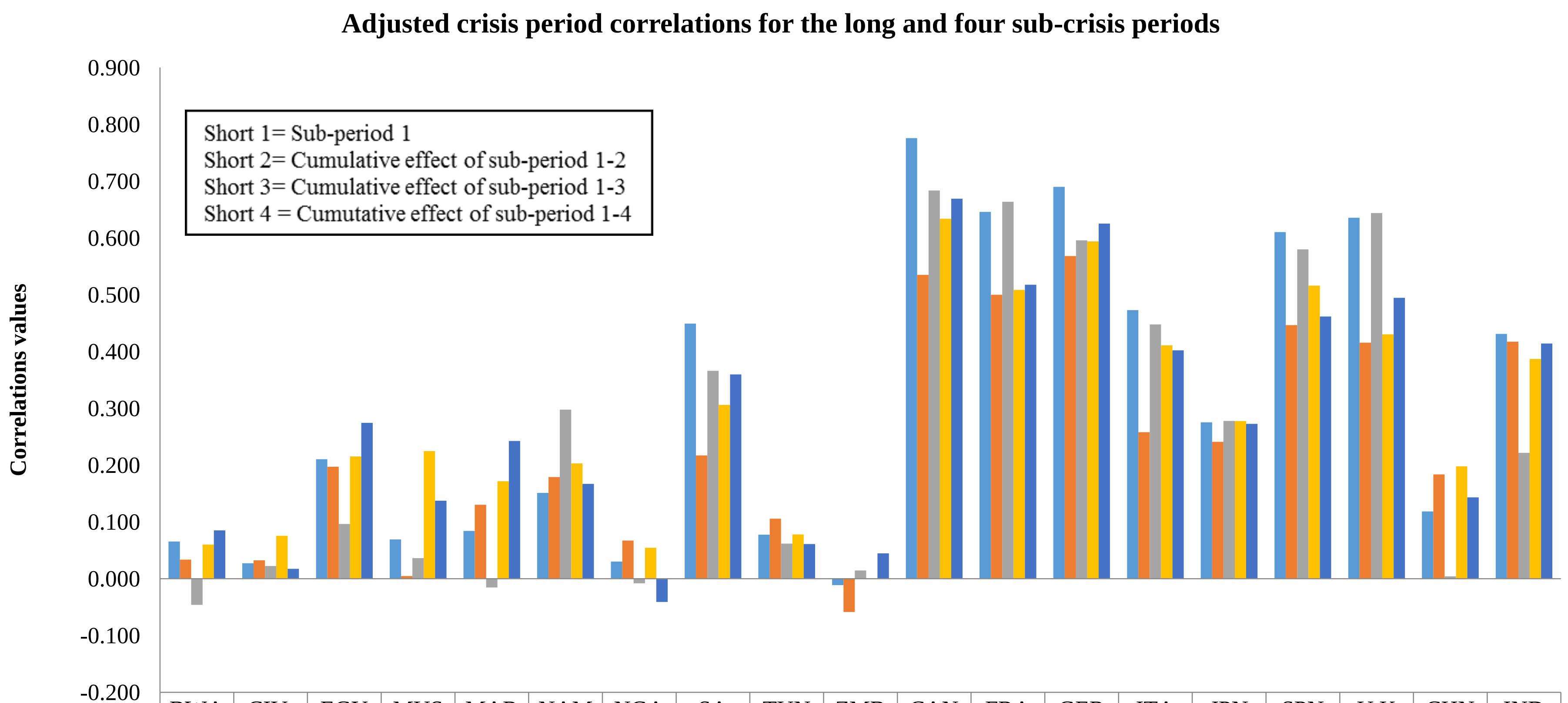
4.6 CHAPTER APPENDICES

Figure A4.1: Stable period correlations with US market from 01/01/2007-14/09/2008 (base case method)



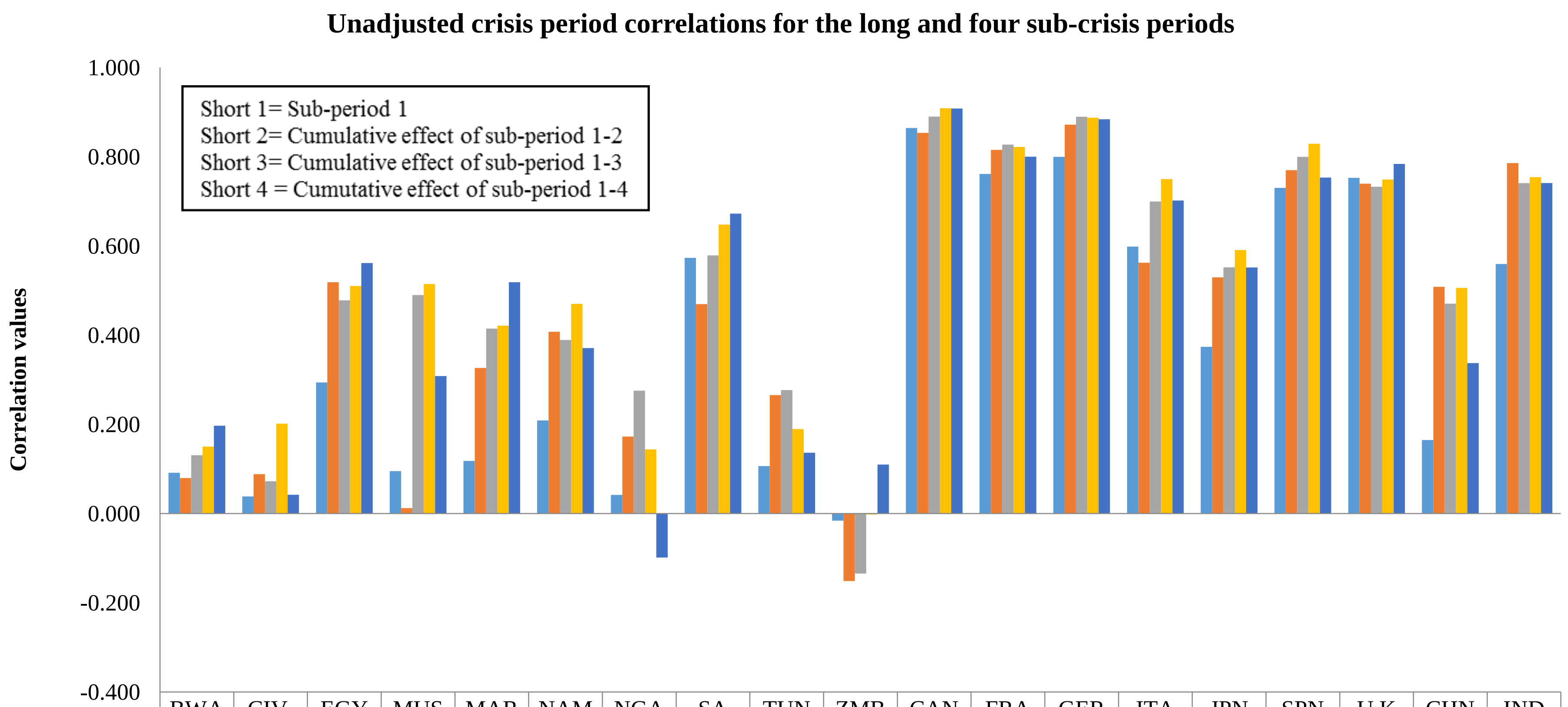
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	-0.042	-0.009	0.248	0.045	-0.020	0.259	-0.017	0.354	0.063	0.003	0.689	0.649	0.583	0.442	0.276	0.561	0.628	-0.002	0.189
Short 1	-0.047	0.022	0.091	0.043	-0.035	0.287	-0.008	0.359	0.079	0.017	0.688	0.655	0.593	0.452	0.276	0.571	0.636	-0.004	0.213
Short 2	-0.046	0.022	0.096	0.036	-0.015	0.298	-0.008	0.366	0.062	0.014	0.684	0.664	0.596	0.448	0.278	0.580	0.644	0.004	0.222
Short 3	-0.049	0.021	0.105	0.040	-0.013	0.292	-0.005	0.360	0.054	0.014	0.681	0.673	0.593	0.448	0.292	0.573	0.648	0.004	0.218
Short 4	-0.047	0.028	0.119	0.054	-0.011	0.286	-0.008	0.350	0.051	0.002	0.690	0.679	0.598	0.455	0.288	0.573	0.647	-0.002	0.221

Figure A4.2: Adjusted crisis period correlations with US market (base case methodology)



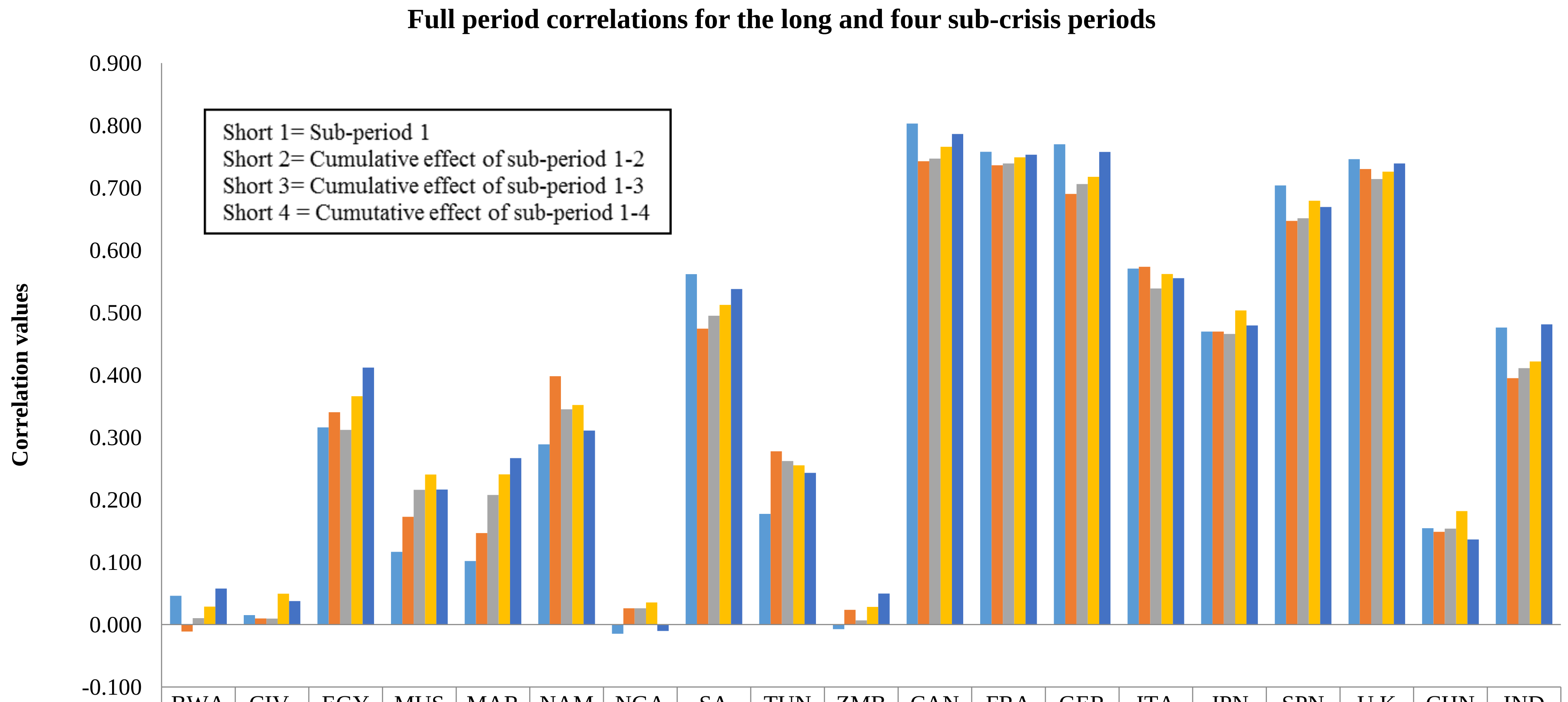
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.066	0.027	0.210	0.069	0.084	0.151	0.030	0.449	0.078	-0.011	0.776	0.646	0.690	0.473	0.275	0.610	0.636	0.119	0.431
Short 1	0.034	0.032	0.197	0.005	0.130	0.179	0.067	0.217	0.106	-0.059	0.535	0.500	0.568	0.258	0.241	0.446	0.416	0.184	0.417
Short 2	-0.046	0.022	0.096	0.036	-0.015	0.298	-0.008	0.366	0.062	0.014	0.684	0.664	0.596	0.448	0.278	0.580	0.644	0.004	0.222
Short 3	0.060	0.076	0.215	0.225	0.172	0.203	0.055	0.306	0.078	-0.001	0.634	0.509	0.594	0.411	0.277	0.516	0.430	0.198	0.387
Short 4	0.085	0.017	0.274	0.137	0.243	0.167	-0.041	0.360	0.061	0.045	0.669	0.518	0.625	0.402	0.273	0.462	0.495	0.143	0.414

Figure A4 3: Unadjusted crisis period correlations with US market (base case methodology)



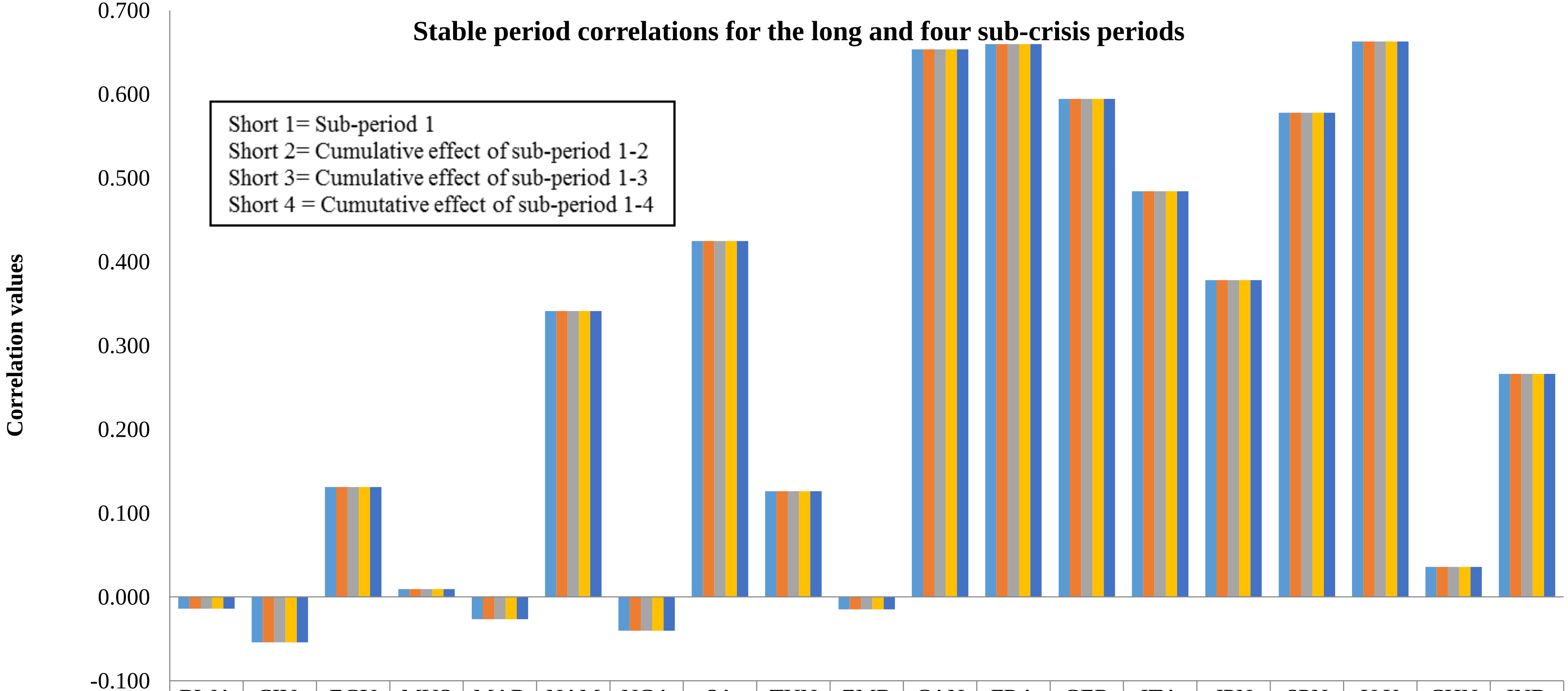
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.091	0.038	0.294	0.095	0.118	0.209	0.042	0.573	0.106	-0.016	0.864	0.761	0.800	0.599	0.374	0.730	0.753	0.165	0.559
Short 1	0.080	0.088	0.519	0.012	0.326	0.408	0.173	0.470	0.266	-0.151	0.853	0.815	0.872	0.562	0.530	0.770	0.740	0.508	0.786
Short 2	0.131	0.073	0.478	0.490	0.415	0.389	0.276	0.579	0.277	-0.134	0.890	0.827	0.890	0.700	0.552	0.800	0.733	0.471	0.741
Short 3	0.150	0.202	0.510	0.514	0.421	0.470	0.144	0.648	0.190	-0.002	0.909	0.822	0.888	0.750	0.591	0.829	0.749	0.506	0.754
Short 4	0.197	0.042	0.562	0.308	0.519	0.371	-0.098	0.673	0.136	0.110	0.908	0.800	0.884	0.702	0.552	0.753	0.784	0.337	0.741

Figure A4.4: Full period correlations with US market (for log returns method covering various periods)



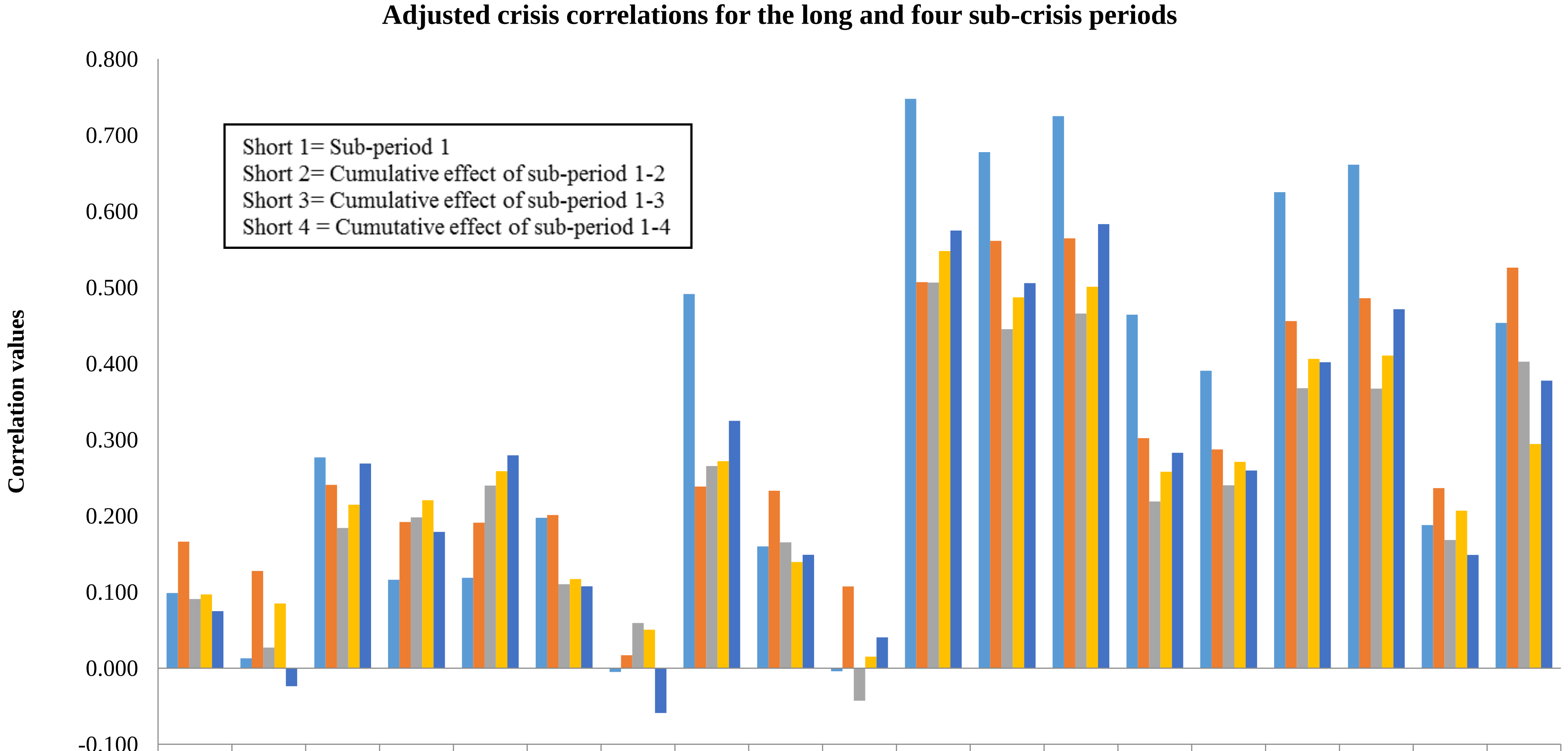
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.046	0.015	0.316	0.117	0.102	0.289	-0.015	0.562	0.178	-0.007	0.803	0.758	0.770	0.571	0.470	0.704	0.746	0.155	0.476
Short 1	-0.011	0.010	0.340	0.173	0.147	0.398	0.026	0.474	0.278	0.024	0.743	0.736	0.690	0.574	0.470	0.647	0.730	0.149	0.395
Short 2	0.010	0.010	0.312	0.216	0.208	0.345	0.026	0.495	0.262	0.007	0.747	0.739	0.706	0.539	0.466	0.651	0.714	0.154	0.411
Short 3	0.029	0.050	0.366	0.240	0.241	0.352	0.035	0.513	0.255	0.028	0.766	0.749	0.718	0.562	0.504	0.680	0.726	0.182	0.422
Short 4	0.058	0.038	0.412	0.217	0.267	0.311	-0.010	0.538	0.243	0.050	0.786	0.753	0.758	0.555	0.479	0.669	0.739	0.137	0.481

Figure A4.5: Stable period correlations with US market from 01/01/2007-14/09/2008 (log returns method)



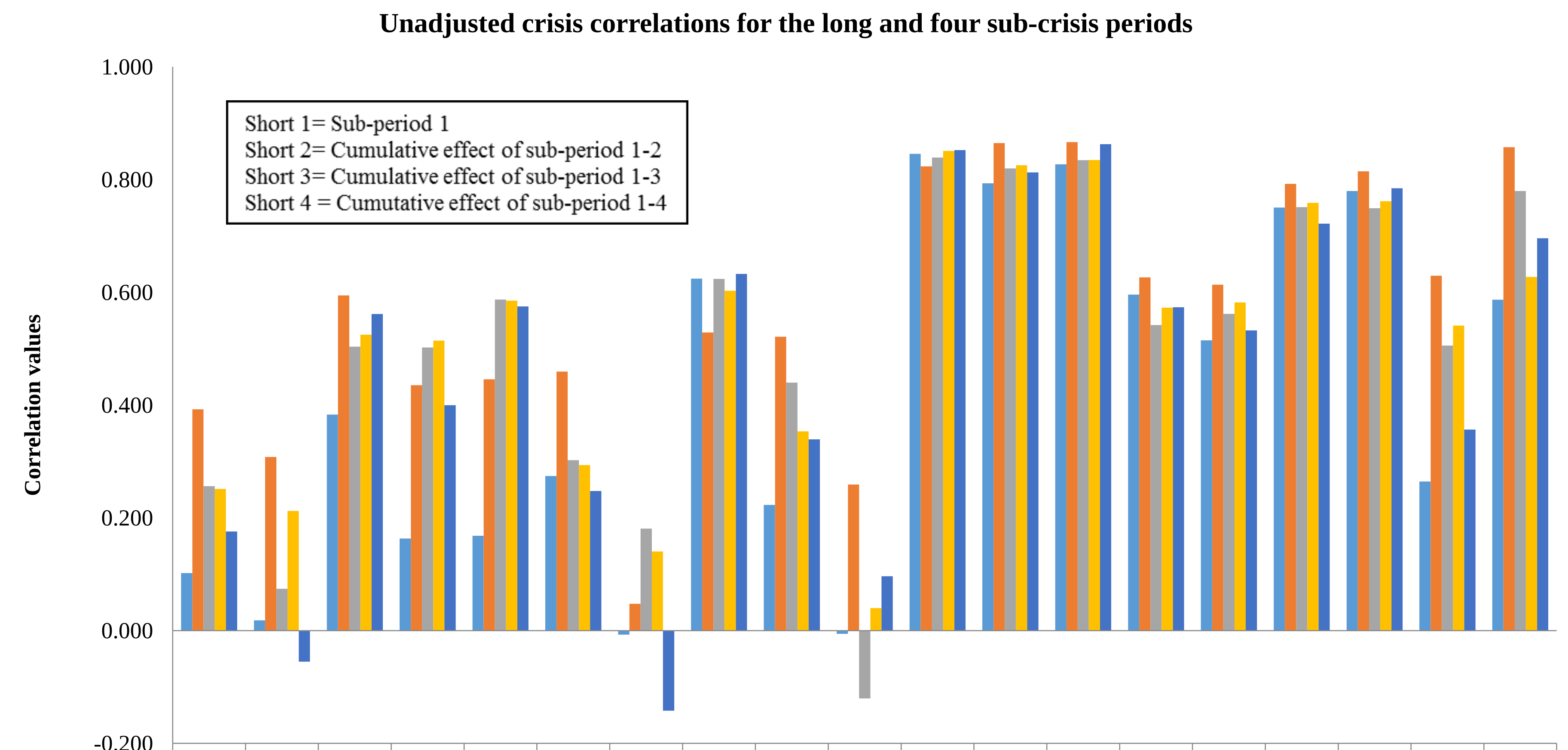
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	-0.014	-0.054	0.131	0.009	-0.027	0.341	-0.040	0.425	0.126	-0.015	0.653	0.660	0.594	0.484	0.378	0.578	0.663	0.036	0.266
Short 1	-0.014	-0.054	0.131	0.009	-0.027	0.341	-0.040	0.425	0.126	-0.015	0.653	0.660	0.594	0.484	0.378	0.578	0.663	0.036	0.266
Short 2	-0.014	-0.054	0.131	0.009	-0.027	0.341	-0.040	0.425	0.126	-0.015	0.653	0.660	0.594	0.484	0.378	0.578	0.663	0.036	0.266
Short 3	-0.014	-0.054	0.131	0.009	-0.027	0.341	-0.040	0.425	0.126	-0.015	0.653	0.660	0.594	0.484	0.378	0.578	0.663	0.036	0.266
Short 4	-0.014	-0.054	0.131	0.009	-0.027	0.341	-0.040	0.425	0.126	-0.015	0.653	0.660	0.594	0.484	0.378	0.578	0.663	0.036	0.266

Figure A4.6: Adjusted crisis Period correlations with US market (log returns methodology)



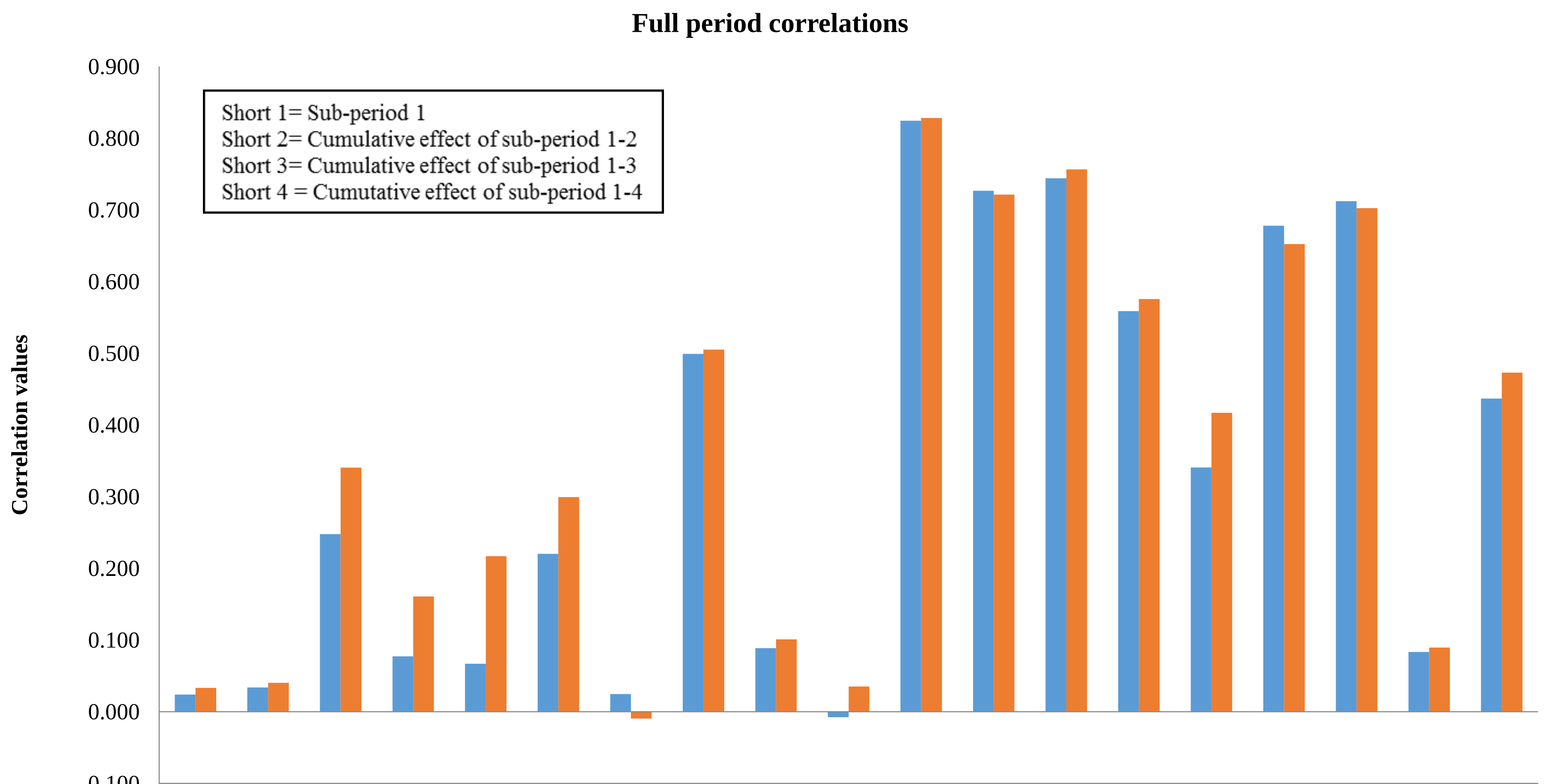
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.099	0.013	0.277	0.116	0.119	0.197	-0.005	0.491	0.160	-0.004	0.748	0.678	0.725	0.464	0.391	0.625	0.661	0.188	0.453
Short 1	0.166	0.128	0.241	0.192	0.191	0.201	0.017	0.238	0.233	0.107	0.507	0.561	0.565	0.302	0.287	0.456	0.486	0.236	0.526
Short 2	0.091	0.027	0.184	0.198	0.240	0.110	0.059	0.265	0.165	-0.043	0.506	0.445	0.466	0.219	0.240	0.368	0.367	0.168	0.403
Short 3	0.097	0.085	0.215	0.220	0.259	0.117	0.051	0.272	0.139	0.015	0.548	0.487	0.501	0.258	0.271	0.406	0.411	0.207	0.294
Short 4	0.075	-0.024	0.269	0.179	0.280	0.107	-0.059	0.325	0.149	0.040	0.575	0.506	0.583	0.283	0.259	0.402	0.471	0.149	0.377

Figure A4.7: Unadjusted crisis period correlations with US market (log returns methodology)



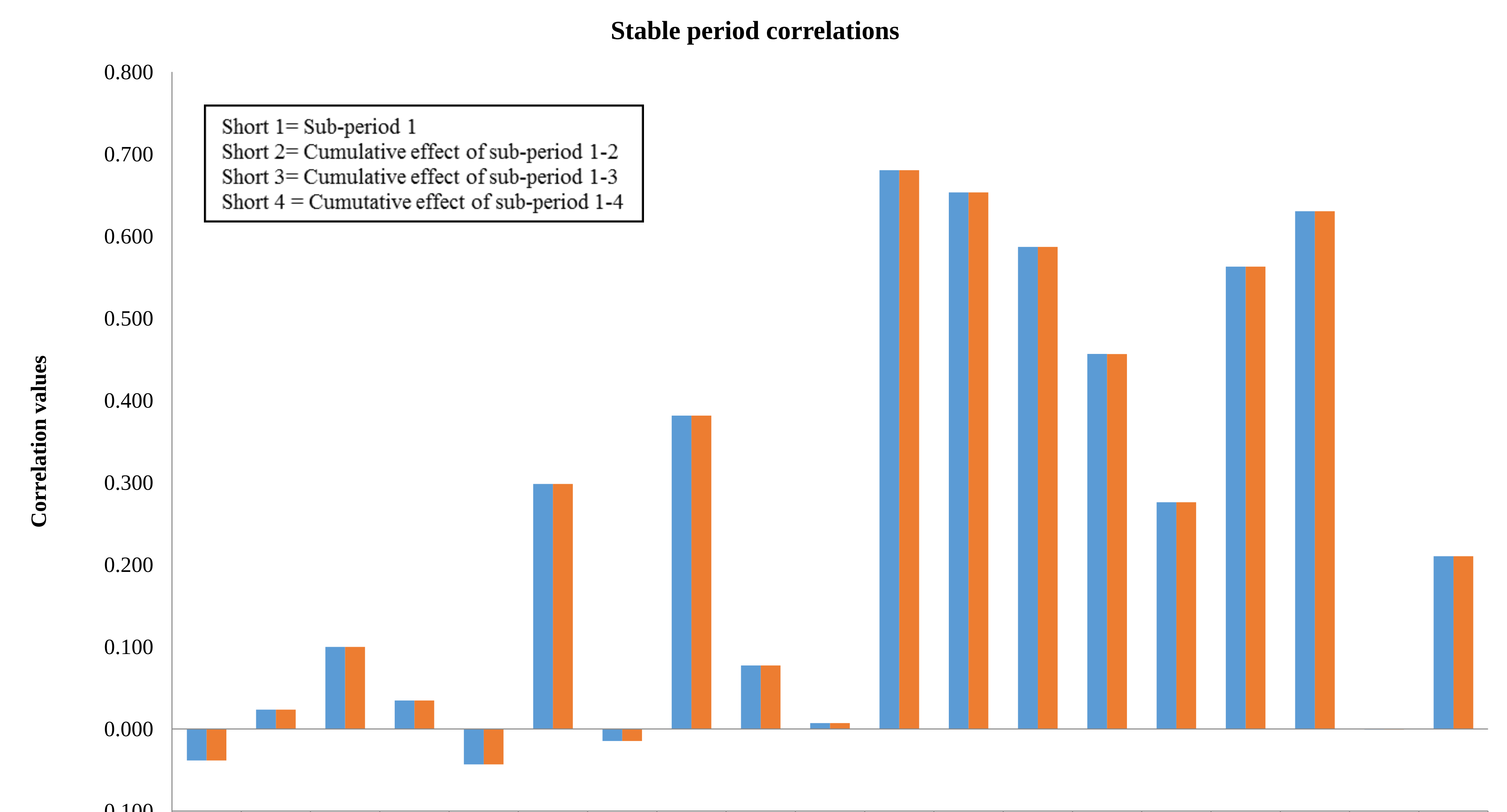
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.102	0.018	0.383	0.163	0.168	0.274	-0.007	0.624	0.223	-0.006	0.846	0.793	0.827	0.596	0.515	0.750	0.780	0.265	0.587
Short 1	0.392	0.308	0.595	0.435	0.446	0.460	0.048	0.529	0.521	0.259	0.823	0.865	0.866	0.627	0.614	0.792	0.815	0.630	0.857
Short 2	0.256	0.074	0.504	0.502	0.587	0.302	0.181	0.624	0.440	-0.120	0.839	0.820	0.835	0.542	0.562	0.751	0.749	0.506	0.780
Short 3	0.251	0.212	0.525	0.514	0.585	0.294	0.140	0.603	0.353	0.040	0.851	0.825	0.835	0.573	0.582	0.759	0.762	0.541	0.627
Short 4	0.176	-0.055	0.561	0.400	0.575	0.248	-0.142	0.633	0.339	0.096	0.852	0.813	0.863	0.573	0.533	0.722	0.785	0.357	0.696

Figure A4.8: Full period correlations with US market separate VAR method (covering various periods)



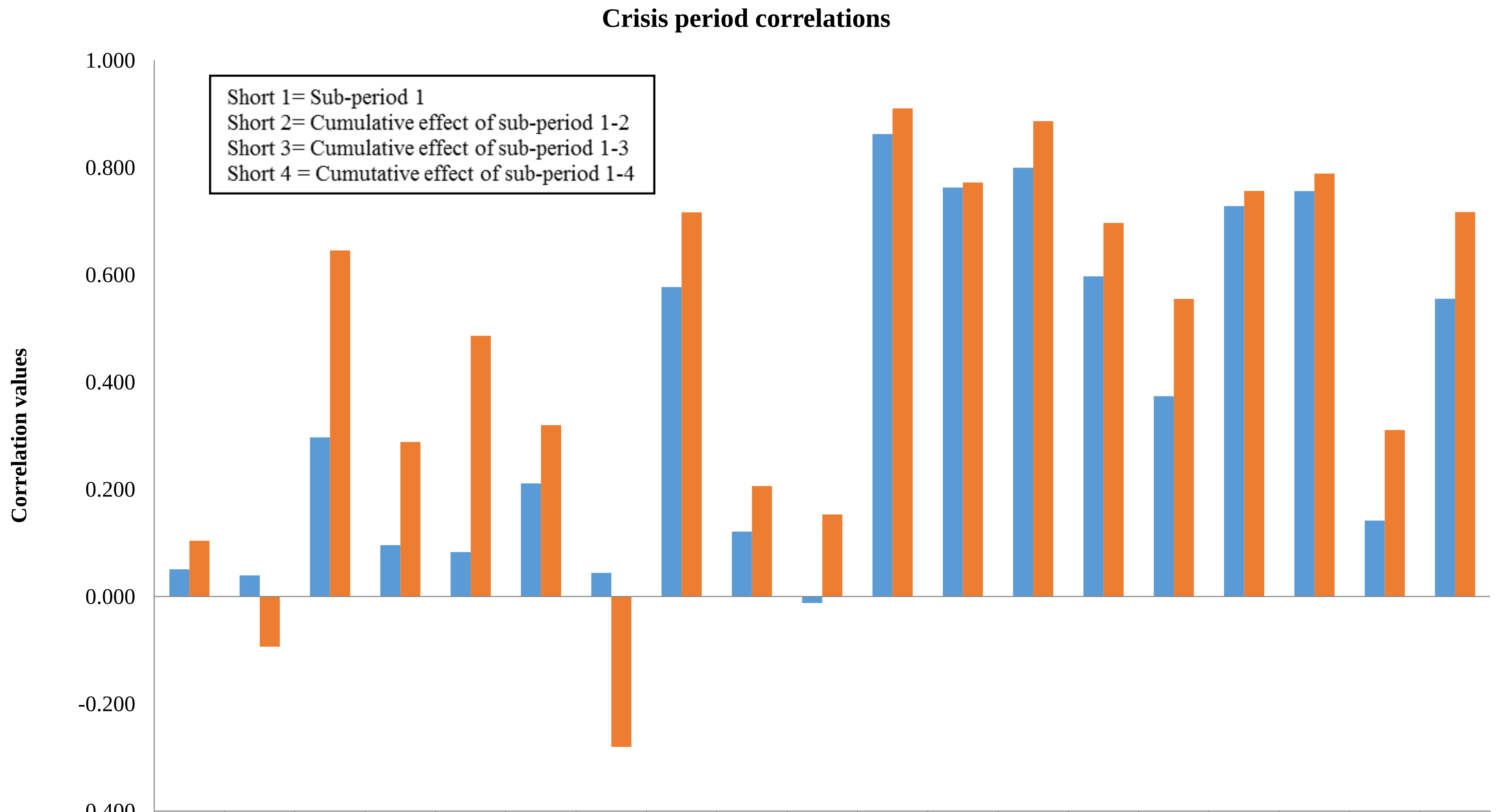
	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.024	0.034	0.248	0.077	0.067	0.220	0.025	0.499	0.089	-0.008	0.824	0.727	0.744	0.559	0.341	0.678	0.712	0.083	0.437
Short 4	0.033	0.040	0.340	0.161	0.217	0.299	-0.010	0.505	0.101	0.035	0.828	0.721	0.757	0.576	0.417	0.652	0.702	0.089	0.473

Figure A4.9: Stable period correlations with US market from 01/01/2007-14/09/2008 (separate VAR method)



	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	-0.038	0.024	0.100	0.035	-0.043	0.298	-0.015	0.382	0.077	0.007	0.680	0.653	0.587	0.457	0.276	0.563	0.630	-0.001	0.210
Short 4	-0.038	0.024	0.100	0.035	-0.043	0.298	-0.015	0.382	0.077	0.007	0.680	0.653	0.587	0.457	0.276	0.563	0.630	-0.001	0.210

Figure A4.10: Crisis period correlations with US market (separate VAR methodology)



	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Long Period	0.051	0.039	0.297	0.096	0.083	0.211	0.044	0.577	0.121	-0.012	0.863	0.763	0.799	0.597	0.374	0.728	0.756	0.142	0.555
Short 4	0.104	-0.094	0.645	0.288	0.486	0.320	-0.281	0.716	0.206	0.153	0.910	0.772	0.887	0.697	0.555	0.756	0.789	0.311	0.717

Table A4.1a: Hypothesis 2 (unadjusted sub-period 1 test from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.047	0.003	0.080	0.005	-0.034	0.003	0.434	NO
Côte d'Ivoire	0.022	0.005	0.088	0.003	0.032	0.005	0.216	NO
Egypt	0.092	0.008	0.519	0.018	0.220	0.008	1.093	NO
Mauritius	0.043	0.006	0.012	0.009	0.050	0.006	-0.150	NO
Morocco	-0.035	0.005	0.326	0.010	0.061	0.005	1.056	NO
Namibia	0.287	0.009	0.408	0.013	0.302	0.009	0.489	NO
Nigeria	-0.008	0.004	0.173	0.002	0.017	0.004	0.560	NO
South Africa	0.359	0.007	0.470	0.017	0.389	0.008	0.389	NO
Tunisia	0.079	0.003	0.266	0.008	0.146	0.004	0.476	NO
Zambia	0.017	0.006	-0.151	0.003	0.017	0.006	-0.685	NO
Developed markets								
Canada	0.688	0.006	0.853	0.019	0.751	0.007	1.182	NO
France	0.655	0.007	0.815	0.017	0.691	0.007	1.189	NO
Germany	0.593	0.006	0.872	0.014	0.657	0.007	**2.236****	**YES**
Italy	0.452	0.005	0.562	0.010	0.480	0.005	0.455	NO
Japan	0.277	0.007	0.530	0.011	0.312	0.007	1.013	NO
Spain	0.571	0.007	0.770	0.017	0.608	0.007	1.271	NO
United Kingdom	0.636	0.006	0.740	0.016	0.667	0.007	0.587	NO
Other markets								
China	-0.004	0.013	0.509	0.019	0.050	0.014	**1.673****	**YES**
India	0.213	0.010	0.786	0.016	0.312	0.010	**2.806*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.1b: Hypothesis 2 (adjusted sub-period 1 test from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.047	0.003	0.034	0.005	-0.034	0.003	0.258	NO
Côte d'Ivoire	0.022	0.005	0.032	0.003	0.032	0.005	0.002	NO
Egypt	0.091	0.008	0.197	0.018	0.220	0.008	-0.074	NO
Mauritius	0.043	0.005	0.005	0.009	0.050	0.006	-0.180	NO
Morocco	-0.035	0.005	0.130	0.010	0.061	0.005	0.265	NO
Namibia	0.287	0.009	0.179	0.013	0.302	0.009	-0.529	NO
Nigeria	-0.008	0.004	0.067	0.002	0.017	0.004	0.179	NO
South Africa	0.359	0.007	0.217	0.017	0.389	0.008	-0.746	NO
Tunisia	0.079	0.003	0.106	0.008	0.146	0.003	-0.156	NO
Zambia	0.017	0.006	-0.059	0.003	0.017	0.006	-0.306	NO
Developed markets								
Canada	0.688	0.006	0.535	0.019	0.751	0.007	-1.532	NO
France	0.655	0.006	0.500	0.017	0.690	0.007	-1.211	NO
Germany	0.593	0.006	0.568	0.014	0.657	0.007	-0.580	NO
Italy	0.452	0.005	0.258	0.010	0.480	0.005	-1.049	NO
Japan	0.277	0.007	0.241	0.011	0.312	0.007	-0.294	NO
Spain	0.571	0.007	0.446	0.017	0.608	0.007	-0.913	NO
United Kingdom	0.636	0.006	0.416	0.016	0.666	0.007	-1.463	NO
Other markets								
China	-0.004	0.013	0.184	0.019	0.050	0.014	0.446	NO
India	0.213	0.010	0.417	0.016	0.312	0.010	0.464	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.2a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-2 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.046	0.003	0.131	0.005	-0.012	0.003	0.613	NO
Côte d'Ivoire	0.022	0.005	0.073	0.003	0.031	0.005	0.182	NO
Egypt	0.096	0.008	0.478	0.017	0.223	0.009	1.076	NO
Mauritius	0.036	0.006	0.490	0.011	0.173	0.006	1.616*	NO
Morocco	-0.015	0.005	0.415	0.010	0.120	0.005	1.403*	NO
Namibia	0.298	0.009	0.389	0.014	0.307	0.009	0.430	NO
Nigeria	-0.008	0.004	0.276	0.003	0.030	0.004	1.024	NO
South Africa	0.366	0.007	0.579	0.017	0.436	0.008	0.866	NO
Tunisia	0.062	0.003	0.277	0.009	0.150	0.004	0.580	NO
Zambia	0.014	0.006	-0.134	0.003	0.011	0.006	-0.668	NO
Developed markets								
Canada	0.684	0.006	0.890	0.021	0.775	0.008	**1.738****	**YES**
France	0.664	0.007	0.827	0.019	0.720	0.008	1.244	NO
Germany	0.596	0.006	0.890	0.019	0.707	0.008	**2.470*****	**YES**
Italy	0.448	0.004	0.700	0.014	0.547	0.005	1.153	NO
Japan	0.278	0.007	0.552	0.018	0.360	0.008	1.042	NO
Spain	0.580	0.007	0.800	0.018	0.642	0.008	1.543*	NO
United Kingdom	0.644	0.006	0.733	0.017	0.678	0.007	0.497	NO
Other markets								
China	0.004	0.013	0.471	0.018	0.075	0.014	**1.709****	**YES**
India	0.222	0.010	0.741	0.023	0.388	0.011	**2.374*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.2b: Hypothesis 2 (Cumulative adjusted test on sub-period 1-2 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.046	0.003	0.048	**0.005**	-0.012	0.003	0.257	NO
Côte d'Ivoire	0.022	0.005	0.025	**0.003**	0.031	0.005	-0.027	NO
Egypt	0.096	0.008	0.181	**0.017**	0.223	0.009	-0.161	NO
Mauritius	0.036	0.006	0.194	0.011	0.173	**0.006**	0.100	NO
Morocco	-0.015	0.005	0.160	0.010	0.120	0.005	0.180	NO
Namibia	0.298	0.009	0.151	0.014	0.307	**0.009**	-0.752	NO
Nigeria	-0.008	0.004	0.095	0.003	0.030	**0.004**	0.265	NO
South Africa	0.366	0.007	0.260	0.017	0.436	**0.008**	-0.902	NO
Tunisia	0.062	0.003	0.107	0.009	0.150	0.004	-0.192	NO
Zambia	0.014	0.006	-0.048	0.003	0.011	0.006	-0.269	NO
Developed markets								
Canada	0.684	0.006	0.577	0.021	0.775	**0.008**	-1.681	NO
France	0.664	0.007	0.488	0.019	0.720	**0.008**	-1.711	NO
Germany	0.596	0.006	0.574	0.019	0.707	**0.008**	-1.039	NO
Italy	0.448	0.004	0.343	0.014	0.547	**0.005**	-1.174	NO
Japan	0.278	0.007	0.233	0.018	0.360	**0.008**	-0.593	NO
Spain	0.580	0.007	0.461	0.018	0.642	**0.008**	-1.198	NO
United Kingdom	0.644	0.006	0.380	0.017	0.678	0.007	-1.950	NO
Other markets								
China	0.004	0.013	0.173	**0.018**	0.075	0.014	0.387	NO
India	0.222	0.010	0.356	0.023	0.388	**0.011**	-0.163	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.3a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-3 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.049	0.003	0.150	0.004	-0.002	0.003	0.747	NO
Côte d'Ivoire	0.021	0.005	0.202	0.003	0.053	0.005	0.748	NO
Egypt	0.105	0.008	0.510	0.017	0.266	0.009	1.200	NO
Mauritius	0.040	0.006	0.514	0.010	0.199	0.006	**1.851****	**YES**
Morocco	-0.013	0.005	0.421	0.010	0.148	0.005	1.488*	NO
Namibia	0.292	0.009	0.470	0.014	0.330	0.010	0.860	NO
Nigeria	-0.005	0.004	0.144	0.002	0.026	0.004	0.556	NO
South Africa	0.360	0.007	0.648	0.017	0.475	0.008	1.287*	NO
Tunisia	0.054	0.003	0.190	0.008	0.123	0.004	0.340	NO
Zambia	0.014	0.006	-0.002	0.003	0.023	0.006	-0.124	NO
Developed markets								
Canada	0.681	0.006	0.909	0.022	0.804	0.008	**2.072****	**YES**
France	0.673	0.007	0.822	0.018	0.724	0.008	1.263	NO
Germany	0.593	0.006	0.888	0.018	0.720	0.008	**2.584*****	**YES**
Italy	0.448	0.004	0.750	0.014	0.588	0.006	1.526	NO
Japan	0.292	0.007	0.591	0.020	0.425	0.008	1.090	NO
Spain	0.573	0.007	0.829	0.019	0.681	0.008	**1.813****	**YES**
United Kingdom	0.648	0.006	0.749	0.016	0.691	0.008	0.625	NO
Other markets								
China	0.004	0.014	0.506	0.018	0.108	0.014	**2.050****	**YES**
India	0.218	0.010	0.754	0.024	0.434	0.011	**2.564*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.3b: Hypothesis 2 (Cumulative adjusted test on sub-period 1- 3 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.049	0.003	0.060	0.004	-0.002	0.003	0.303	NO
Côte d'Ivoire	0.021	0.005	0.076	0.003	0.053	0.005	0.111	NO
Egypt	0.105	0.008	0.215	0.017	0.266	0.009	-0.224	NO
Mauritius	0.040	0.006	0.225	0.010	0.199	0.006	0.136	NO
Morocco	-0.013	0.005	0.172	0.010	0.148	0.005	0.123	NO
Namibia	0.292	0.009	0.203	0.014	0.330	0.010	-0.700	NO
Nigeria	-0.005	0.004	0.055	0.002	0.026	0.004	0.135	NO
South Africa	0.360	0.007	0.306	0.017	0.475	0.008	-1.009	NO
Tunisia	0.054	0.003	0.078	0.008	0.123	0.004	-0.223	NO
Zambia	0.014	0.006	-0.001	0.003	0.023	0.006	-0.118	NO
Developed markets								
Canada	0.681	0.006	0.634	0.022	0.804	0.008	-1.823	NO
France	0.673	0.007	0.509	0.018	0.724	0.008	-1.827	NO
Germany	0.593	0.006	0.594	0.018	0.720	0.008	-1.146	NO
Italy	0.448	0.004	0.411	0.014	0.588	0.006	-1.221	NO
Japan	0.292	0.007	0.277	0.020	0.425	0.008	-0.823	NO
Spain	0.573	0.007	0.516	0.019	0.681	0.008	-1.336	NO
United Kingdom	0.648	0.006	0.430	0.016	0.691	0.008	-1.995	NO
Other markets								
China	0.004	0.014	0.198	0.018	0.108	0.014	0.420	NO
India	0.218	0.010	0.387	0.024	0.434	0.011	-0.281	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.4a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-4 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.047	0.003	0.197	0.004	0.033	0.003	1.041	NO
Côte d'Ivoire	0.028	0.005	0.042	0.004	0.040	0.005	0.012	NO
Egypt	0.119	0.008	0.562	0.017	0.340	0.009	1.520*	NO
Mauritius	0.054	0.005	0.308	0.009	0.161	0.006	0.990	NO
Morocco	-0.011	0.005	0.519	0.009	0.217	0.005	**2.193****	**YES**
Namibia	0.286	0.009	0.371	0.015	0.299	0.010	0.522	NO
Nigeria	-0.008	0.004	-0.098	0.005	-0.010	0.004	-0.546	NO
South Africa	0.350	0.007	0.673	0.017	0.505	0.009	**1.660****	**YES**
Tunisia	0.051	0.003	0.136	0.007	0.101	0.004	0.225	NO
Zambia	0.002	0.006	0.110	0.004	0.035	0.006	0.466	NO
Developed markets								
Canada	0.690	0.006	0.908	0.022	0.828	0.009	**2.141****	**YES**
France	0.679	0.007	0.800	0.016	0.721	0.008	1.222	NO
Germany	0.598	0.006	0.884	0.020	0.757	0.009	**2.623*****	**YES**
Italy	0.455	0.004	0.702	0.013	0.576	0.006	1.390*	NO
Japan	0.288	0.007	0.552	0.020	0.417	0.009	1.096	NO
Spain	0.573	0.007	0.753	0.017	0.652	0.008	1.301*	NO
United Kingdom	0.647	0.006	0.784	0.016	0.702	0.008	1.184	NO
Other markets								
China	-0.002	0.013	0.337	0.017	0.089	0.014	1.581*	NO
India	0.221	0.010	0.741	0.023	0.473	0.012	**2.722*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.4b: Hypothesis 2 (Cumulative adjusted test on sub-period 1-4 from a single VAR)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.047	0.003	0.085	0.004	0.033	0.003	0.326	NO
Côte d'Ivoire	0.028	0.005	0.017	0.004	0.040	0.005	-0.144	NO
Egypt	0.119	0.008	0.274	0.017	0.340	0.009	-0.396	NO
Mauritius	0.054	0.005	0.137	0.009	0.161	0.006	-0.152	NO
Morocco	-0.011	0.005	0.243	0.009	0.217	0.005	0.168	NO
Namibia	0.286	0.009	0.167	0.015	0.299	0.010	-0.906	NO
Nigeria	-0.008	0.004	-0.041	0.005	-0.010	0.004	-0.192	NO
South Africa	0.350	0.007	0.360	0.017	0.505	0.009	-1.149	NO
Tunisia	0.051	0.003	0.061	0.007	0.101	0.004	-0.250	NO
Zambia	0.002	0.006	0.045	0.004	0.035	0.006	0.059	NO
Developed markets								
Canada	0.690	0.006	0.669	0.022	0.828	0.009	-2.387	NO
France	0.679	0.007	0.518	0.016	0.721	0.008	-2.180	NO
Germany	0.598	0.006	0.625	0.020	0.757	0.009	-1.645	NO
Italy	0.455	0.004	0.402	0.013	0.576	0.006	-1.485	NO
Japan	0.288	0.007	0.273	0.020	0.417	0.009	-1.016	NO
Spain	0.573	0.007	0.462	0.017	0.652	0.008	-1.809	NO
United Kingdom	0.647	0.006	0.495	0.016	0.702	0.008	-2.134	NO
Other markets								
China	-0.002	0.013	0.143	0.017	0.089	0.014	0.330	NO
India	0.221	0.010	0.414	0.023	0.473	0.012	-0.454	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.5a: Hypothesis 2 (unadjusted sub-period 1 test using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.014	0.005	0.392	0.007	-0.011	0.005	1.621*	NO
Côte d'Ivoire	-0.054	0.006	0.308	0.002	0.010	0.006	1.174	NO
Egypt	0.131	0.011	0.595	0.026	0.340	0.013	1.029	NO
Mauritius	0.009	0.008	0.435	0.015	0.173	0.009	1.147	NO
Morocco	-0.027	0.007	0.446	0.019	0.147	0.008	1.262	NO
Namibia	0.341	0.013	0.460	0.024	0.398	0.014	0.304	NO
Nigeria	-0.040	0.009	0.048	0.002	0.026	0.009	0.076	NO
South Africa	0.425	0.010	0.529	0.019	0.474	0.011	0.287	NO
Tunisia	0.126	0.005	0.521	0.010	0.278	0.005	1.114	NO
Zambia	-0.015	0.008	0.259	0.003	0.024	0.008	0.976	NO
Developed markets								
Canada	0.653	0.007	0.823	0.024	0.743	0.009	0.853	NO
France	0.660	0.009	0.865	0.024	0.736	0.010	1.494*	NO
Germany	0.594	0.000	0.866	0.000	0.690	0.010	**1.900****	**YES**
Italy	0.484	0.007	0.627	0.019	0.574	0.009	0.336	NO
Japan	0.378	0.010	0.614	0.019	0.470	0.011	0.780	NO
Spain	0.578	0.009	0.792	0.024	0.647	0.010	1.243	NO
United Kingdom	0.663	0.008	0.815	0.024	0.730	0.010	0.855	NO
Other markets								
China	0.036	0.018	0.630	0.034	0.149	0.018	**1.934****	**YES**
India	0.266	0.014	0.857	0.023	0.395	0.015	**3.296*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.5b: Hypothesis 2 (adjusted sub-period 1 test using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.014	0.005	0.166	0.007	-0.011	0.005	0.681	NO
Côte d'Ivoire	-0.054	0.006	0.128	0.002	0.010	0.006	0.451	NO
Egypt	0.131	0.011	0.241	0.026	0.340	0.013	-0.339	NO
Mauritius	0.009	0.008	0.192	0.015	0.173	0.009	0.078	NO
Morocco	-0.027	0.007	0.191	0.019	0.147	0.008	0.173	NO
Namibia	0.341	0.013	0.201	0.024	0.398	0.014	-0.881	NO
Nigeria	-0.040	0.009	0.017	0.002	0.026	0.009	-0.033	NO
South Africa	0.425	0.010	0.238	0.019	0.474	0.011	-1.070	NO
Tunisia	0.126	0.005	0.233	0.010	0.278	0.005	-0.182	NO
Zambia	-0.015	0.008	0.107	0.003	0.024	0.008	0.339	NO
Developed markets								
Canada	0.653	0.007	0.507	0.024	0.743	0.009	-1.610	NO
France	0.660	0.009	0.561	0.024	0.736	0.010	-1.245	NO
Germany	0.594	0.000	0.565	0.000	0.690	0.010	-0.846	NO
Italy	0.484	0.007	0.302	0.019	0.574	0.009	-1.379	NO
Japan	0.378	0.010	0.287	0.019	0.470	0.011	-0.815	NO
Spain	0.578	0.009	0.456	0.024	0.647	0.010	-1.127	NO
United Kingdom	0.663	0.008	0.486	0.024	0.730	0.010	-1.612	NO
Other markets								
China	0.036	0.018	0.236	0.034	0.149	0.018	0.298	NO
India	0.266	0.014	0.526	0.023	0.395	0.015	0.635	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table 4A.6a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-2 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.014	0.005	0.256	0.007	0.010	0.005	1.073	NO
Côte d'Ivoire	-0.054	0.006	0.074	0.003	0.010	0.006	0.282	NO
Egypt	0.131	0.011	0.504	0.026	0.312	0.013	0.848	NO
Mauritius	0.009	0.008	0.502	0.020	0.216	0.009	1.488*	NO
Morocco	-0.027	0.007	0.587	0.019	0.208	0.008	**2.023****	**YES**
Namibia	0.341	0.013	0.302	0.025	0.345	0.014	-0.218	NO
Nigeria	-0.040	0.009	0.181	0.003	0.026	0.009	0.633	NO
South Africa	0.425	0.010	0.624	0.021	0.495	0.011	0.844	NO
Tunisia	0.126	0.005	0.440	0.011	0.262	0.005	0.890	NO
Zambia	-0.015	0.008	-0.120	0.003	0.007	0.008	-0.584	NO
Developed markets								
Canada	0.653	0.007	0.839	0.025	0.747	0.010	1.127	NO
France	0.660	0.009	0.820	0.030	0.739	0.011	0.952	NO
Germany	0.594	0.009	0.835	0.027	0.706	0.011	1.481*	NO
Italy	0.484	0.007	0.542	0.027	0.539	0.010	0.021	NO
Japan	0.378	0.010	0.562	0.027	0.466	0.012	0.556	NO
Spain	0.578	0.009	0.751	0.027	0.651	0.011	0.906	NO
United Kingdom	0.663	0.008	0.749	0.027	0.714	0.011	0.345	NO
Other markets								
China	0.036	0.018	0.506	0.030	0.154	0.018	1.577*	NO
India	0.266	0.014	0.780	0.025	0.411	0.015	**2.657*****	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.6b: Hypothesis 2 (Cumulative adjusted test on sub-period 1-2 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	ρ	σ	ρ	σ		
Botswana	-0.014	0.005	0.091	0.007	0.010	0.005	0.344	NO
Côte d'Ivoire	-0.054	0.006	0.027	0.003	0.010	0.006	0.076	NO
Egypt	0.131	0.011	0.184	0.026	0.312	0.013	-0.501	NO
Mauritius	0.009	0.008	0.198	0.020	0.216	0.009	-0.085	NO
Morocco	-0.027	0.007	0.240	0.019	0.208	0.008	0.148	NO
Namibia	0.341	0.013	0.110	0.025	0.345	0.014	-1.140	NO
Nigeria	-0.040	0.009	0.059	0.003	0.026	0.009	0.134	NO
South Africa	0.425	0.010	0.265	0.021	0.495	0.011	-1.213	NO
Tunisia	0.126	0.005	0.165	0.011	0.262	0.005	-0.445	NO
Zambia	-0.015	0.008	-0.043	0.003	0.007	0.008	-0.227	NO
Developed markets								
Canada	0.653	0.007	0.506	0.025	0.747	0.010	-1.829	NO
France	0.660	0.009	0.445	0.030	0.739	0.011	-2.152	NO
Germany	0.594	0.009	0.466	0.027	0.706	0.011	-1.716	NO
Italy	0.484	0.007	0.219	0.027	0.539	0.010	-1.740	NO
Japan	0.378	0.010	0.240	0.027	0.466	0.012	-1.109	NO
Spain	0.578	0.009	0.368	0.027	0.651	0.011	-1.794	NO
United Kingdom	0.663	0.008	0.367	0.027	0.714	0.011	-2.337	NO
Other markets								
China	0.036	0.018	0.168	0.030	0.154	0.018	0.058	NO
India	0.266	0.014	0.403	0.025	0.411	0.015	-0.044	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.7a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-3 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.014	0.005	0.251	0.006	0.029	0.005	1.109	NO
Côte d'Ivoire	-0.054	0.006	0.212	0.004	0.050	0.006	0.821	NO
Egypt	0.131	0.011	0.525	0.027	0.366	0.013	0.824	NO
Mauritius	0.009	0.008	0.514	0.019	0.240	0.009	1.630*	NO
Morocco	-0.027	0.007	0.585	0.018	0.241	0.008	**2.105****	**YES**
Namibia	0.341	0.013	0.294	0.025	0.352	0.014	-0.335	NO
Nigeria	-0.040	0.009	0.140	0.002	0.035	0.009	0.494	NO
South Africa	0.425	0.010	0.603	0.023	0.513	0.012	0.662	NO
Tunisia	0.126	0.005	0.353	0.010	0.255	0.005	0.536	NO
Zambia	-0.015	0.008	0.040	0.004	0.028	0.008	0.059	NO
Developed markets								
Canada	0.653	0.007	0.851	0.028	0.766	0.010	1.252	NO
France	0.660	0.009	0.825	0.029	0.749	0.012	1.043	NO
Germany	0.594	0.009	0.835	0.025	0.718	0.011	1.543*	NO
Italy	0.484	0.007	0.573	0.026	0.562	0.010	0.081	NO
Japan	0.378	0.010	0.582	0.031	0.504	0.013	0.543	NO
Spain	0.578	0.009	0.759	0.029	0.680	0.012	0.846	NO
United Kingdom	0.663	0.008	0.762	0.027	0.726	0.011	0.410	NO
Other markets								
China	0.036	0.018	0.541	0.028	0.182	0.018	**1.929****	**YES**
India	0.266	0.014	0.627	0.029	0.422	0.016	1.422*	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.7b: Hypothesis 2 (Cumulative adjusted test on sub-period 1-3 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.014	0.005	0.097	0.006	0.029	0.005	0.333	NO
Côte d'Ivoire	-0.054	0.006	0.085	0.004	0.050	0.006	0.176	NO
Egypt	0.131	0.011	0.215	0.027	0.366	0.013	-0.686	NO
Mauritius	0.009	0.008	0.221	0.019	0.240	0.009	-0.106	NO
Morocco	-0.027	0.007	0.259	0.018	0.241	0.008	0.095	NO
Namibia	0.341	0.013	0.117	0.025	0.352	0.014	-1.283	NO
Nigeria	-0.040	0.009	0.051	0.002	0.035	0.009	0.071	NO
South Africa	0.425	0.010	0.272	0.023	0.513	0.012	-1.449	NO
Tunisia	0.126	0.005	0.139	0.010	0.255	0.005	-0.599	NO
Zambia	-0.015	0.008	0.015	0.004	0.028	0.008	-0.068	NO
Developed markets								
Canada	0.653	0.007	0.548	0.028	0.766	0.010	-1.994	NO
France	0.660	0.009	0.487	0.029	0.749	0.012	-2.251	NO
Germany	0.594	0.009	0.501	0.025	0.718	0.011	-1.811	NO
Italy	0.484	0.007	0.258	0.026	0.562	0.010	-1.909	NO
Japan	0.378	0.010	0.271	0.031	0.504	0.013	-1.342	NO
Spain	0.578	0.009	0.406	0.029	0.680	0.012	-2.039	NO
United Kingdom	0.663	0.008	0.411	0.027	0.726	0.011	-2.483	NO
Other markets								
China	0.036	0.018	0.207	0.028	0.182	0.018	0.118	NO
India	0.266	0.014	0.294	0.029	0.422	0.016	-0.727	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.8a: Hypothesis 2 (Cumulative unadjusted test on sub-period 1-4 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.014	0.005	0.176	0.006	0.058	0.005	0.751	NO
Côte d'Ivoire	-0.054	0.006	-0.055	0.005	0.038	0.007	-0.587	NO
Egypt	0.131	0.011	0.561	0.028	0.412	0.014	1.068	NO
Mauritius	0.009	0.008	0.400	0.015	0.217	0.009	1.287*	NO
Morocco	-0.027	0.007	0.575	0.015	0.267	0.008	**2.365*** **	**YES**
Namibia	0.341	0.013	0.248	0.027	0.311	0.015	-0.445	NO
Nigeria	-0.040	0.009	-0.142	0.014	-0.010	0.010	-0.815	NO
South Africa	0.425	0.010	0.633	0.024	0.538	0.012	0.926	NO
Tunisia	0.126	0.005	0.339	0.009	0.243	0.005	0.658	NO
Zambia	-0.015	0.008	0.096	0.005	0.050	0.008	0.290	NO
Developed markets								
Canada	0.653	0.007	0.852	0.027	0.786	0.012	1.296*	NO
France	0.660	0.009	0.813	0.028	0.753	0.013	1.001	NO
Germany	0.594	0.009	0.863	0.027	0.758	0.012	**2.030** **	**YES**
Italy	0.484	0.007	0.573	0.025	0.555	0.011	0.172	NO
Japan	0.378	0.010	0.533	0.033	0.479	0.014	0.443	NO
Spain	0.578	0.009	0.722	0.029	0.670	0.013	0.657	NO
United Kingdom	0.663	0.008	0.785	0.027	0.739	0.012	0.704	NO
Other markets								
China	0.036	0.018	0.357	0.025	0.137	0.019	1.427*	NO
India	0.266	0.014	0.696	0.032	0.481	0.017	**2.076** **	**YES**

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

Table A4.8b: Hypothesis 2 (Cumulative adjusted test on sub- period 1-4 using log returns)

African markets	Stable period		Crisis period		Full period		Test statistics	Evidence of contagion?
	ρ	σ	*ρ*	σ	*ρ*	σ		
Botswana	-0.014	0.005	0.075	0.006	0.058	0.005	0.108	NO
Côte d'Ivoire	-0.054	0.006	-0.024	0.005	0.038	0.007	-0.389	NO
Egypt	0.131	0.011	0.269	0.028	0.412	0.014	-0.880	NO
Mauritius	0.009	0.008	0.179	0.015	0.217	0.009	-0.248	NO
Morocco	-0.027	0.007	0.280	0.015	0.267	0.008	0.085	NO
Namibia	0.341	0.013	0.107	0.027	0.311	0.015	-1.383	NO
Nigeria	-0.040	0.009	-0.059	0.014	-0.010	0.010	-0.300	NO
South Africa	0.425	0.010	0.325	0.024	0.538	0.012	-1.692	NO
Tunisia	0.126	0.005	0.149	0.009	0.243	0.005	-0.616	NO
Zambia	-0.015	0.008	0.040	0.005	0.050	0.008	-0.058	NO
Developed markets								
Canada	0.653	0.007	0.575	0.027	0.786	0.012	-2.609	NO
France	0.660	0.009	0.506	0.028	0.753	0.013	-2.741	NO
Germany	0.594	0.009	0.583	0.027	0.758	0.012	-2.091	NO
Italy	0.484	0.007	0.283	0.025	0.555	0.011	-2.169	NO
Japan	0.378	0.010	0.259	0.033	0.479	0.014	-1.590	NO
Spain	0.578	0.009	0.402	0.029	0.670	0.013	-2.485	NO
United Kingdom	0.663	0.008	0.471	0.027	0.739	0.012	-2.825	NO
Other markets								
China	0.036	0.018	0.149	0.025	0.137	0.019	0.075	NO
India	0.266	0.014	0.377	0.032	0.481	0.017	-0.791	NO

*Significant at 10%, **Significant at 5%, ***Significant at 1%. Contagion is defined as statistical significance at 5% level.

5 CONTAGION TEST: A TIME-VARYING CORRELATION ANALYSIS

5.1 INTRODUCTION

It was identified in Chapter 2 that researchers have identified potential problems in respect to applying the static correlation model to contagion analysis. These arguments have been supported by my findings from Chapter 4. The issues raised relate to the adjustments to the standard error made by Forbes and Rigobon (2002) in order to control for the excess volatility during crisis periods and also relate to their use of a single-system VAR.

Another issue that researchers face is that the static correlation models fail to take into consideration fluctuations in correlation over time. I believe that this is a particularly important issue in respect to the 2007-09 financial crisis, given that it ran over a relatively long period, and therefore considerable changes in correlation might be expected.

In this chapter, I attempt to address both of these issues by testing for contagion using a time-varying correlations measure using the DCC-MGARCH framework of Engle (2002). The results of these tests are presented in summary or stylised fact form in this chapter. They will be discussed from a behavioural perspective and compared (and contrasted) with the static correlations tests undertaken in the previous chapter, in Chapter 6.

5.2 CHAPTER AIMS AND HYPOTHESES

This chapter explores the same hypotheses as were tested in Chapter 4 (see Section 4.1). The primary objective is to identify if the use of a more sophisticated methodology will produce appreciably different findings. This is important given the criticisms and issues associated with the static-correlation-based approach. The rationales for the hypotheses tested are detailed in Chapter 3. The hypotheses tested are:

Hypothesis 1

Hypothesis 1a: There is a statistically significant increase in correlations between US and developed markets over the period 15 September 2008-15 October 2009.

Hypothesis 1b: There is a statistically significant increase in correlations between US and African markets over the period 15 September 2008-15 October 2009.

Hypothesis 2

Hypothesis 2a: There is a statistically significant increase in correlations between US and developed markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

Hypothesis 2b: There is a statistically significant increase in correlations between US and African markets over the sub-periods 15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008.

5.3 TIME-VARYING CORRELATION METHODOLOGY

The time-varying methodology adopted in this section is the DCC-MGARCH model. Unlike the static model, this methodology enables us to estimate correlations at each point in time. This is done through estimating conditional covariance and conditional variances at each point in time.

$$\rho_{ij,t} = \frac{\text{Conditional Covariance}_{ij,t}}{\sqrt{\text{conditional variance}_{it}\text{conditional variance}_{jt}}} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \quad (5.1)$$

where $i =$ US and $j =$ a second country.

The covariance and variance terms are estimated from the covariance matrix Q_t, where $Q_t = [q_{ij,t}]$

5.3.1 Estimating conditional correlations using the multivariate DCC model

The model applied is based on a variant of the original dynamic conditional correlation multivariate GARCH model proposed by Engle (2002). This methodology can be run on the basis of either a system of equations or on the basis of a series of equation pairs, where the equation pairs are the US market and "a second country". I run the model on the basis of 19 equation pairs, given the objective is to identify contagion between the US and individual countries. These countries are grouped into African markets, developed markets and "others", as shown in Table 5.1 below.

The first step in this pairs-based modelling procedure is to estimate the residual returns mean equations. These equations, which are in a VAR format (the mean equation form is discussed below), are as follows:

$$r_{it} = \mu_i + \sum_{k=1}^{m} \alpha_{ik}\, r_{it-k} + \sum_{k=1}^{m} \beta_{ik}\, r_{jt-k} + \varepsilon_{it} \qquad (5.2)$$

$$r_{jt} = \mu_j + \sum_{k=1}^{m} \alpha_{jk}\, r_{jt-k} + \sum_{k=1}^{m} \beta_{jk}\, r_{it-k} + \varepsilon_{jt} \qquad (5.3)$$

where i represent the US and j a second country.

The methodology assumes that residuals are conditionally multivariate-normal.

The residuals from the mean equation pairs are then used to derive the variance equations. These are in a GARCH (1, 1) format (discussed below). They are as follows:

$$\sigma_{it}^2 = \alpha_{i0} + \alpha_{i1}\, \varepsilon_{it-1}^2 + \beta_{i1}\sigma_{it-1}^2 \qquad (5.4)$$

$$\sigma_{jt}^2 = \alpha_{j0} + \alpha_{j1}\, \varepsilon_{jt-1}^2 + \beta_{j1}\sigma_{jt-1}^2 \qquad (5.5)$$

where σ_t^2 is the conditional variance, α_0 the intercept, ε the standardised residuals, α_1 represents the ARCH parameter and β_1 the GARCH parameter.

The correlation coefficients are estimated from the DCC equation:

$$\mathrm{Q_t} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha \nu_{t-1}\nu'_{t-1} + \beta \mathrm{Q}_{t-1} \qquad (5.6)$$

where Q_t represents the covariance matrix, $Q_t = [\mathrm{q}_{ij,t}]$, and ν_t represents the residuals standardised by their conditional standard deviation. The model is mean reverting as long as the non-negative scalars satisfy the constraint $\alpha + \beta < 1$

A significant alpha coefficient value in the DCC equation is an indication that correlations will vary appreciably over time. It can be noted in Appendix Tables A5.2b, A5.2d and A5.2f that the alpha parameter is significant in all cases except Mauritius, Nigeria, Tunisia and Zambia. This is indicative that there is a likelihood that evidence of contagion could be found within the data. This is because it indicates significant changes in the conditional correlation over time in most of the sample countries. The beta parameter is an estimate of the persistence[26] within the series. If $\alpha + \beta = 1$, the model will not mean revert, which would effectively mean the series would be integrated to the order 1: i.e. I (1). In the case of our models presented in Appendix Table A5.2, this does not present major issues.

5.3.2 Development of the VAR-based mean equations

The mean equations developed are presented in Appendix Tables A5.1a to A5.1f. Unlike standard mean equations, which contain a single constant, these are based on VAR equations. This approach is taken for two reasons. First, following Forbes and Rigobon (2002), in order to identify contagion between two series, the residuals used to estimate the correlation must control for (eliminate) all other (non-contagion-based) factors that can influence returns. As Forbes and Rigobon (2002) show us, these are in effect the lagged returns in the two markets concerned.

Although Forbes and Rigobon (2002) concluded that a five-lag VAR structure was sufficient to control for non-contagion factors, there is also an additional issue that needs to be considered in respect to the MGARCH-DCC model. Tsay (2005) showed that evidence of autocorrelation in the residuals of either the mean or variance equations

[26] Persistence is measured as the half-life of shock computed as $\ln(0.5)/\ln(\alpha+\beta)$ as suggested in Engle and Sheppard (2001). The half-life is defined as the time at which a shock to correlation is expected to be halfway dissipated.

would compromise the integrity of the methodology. On this basis I had to identify an optimal lag structure of the VAR that was subject to the condition that there was an absence of autocorrelation in these two series of equations. This process of testing for autocorrelation is described in Section 5.3.3 below.

The optimal lag-length selection was undertaken using information criteria. Three selection criteria are used for this purpose, namely AIC,[27] BIC[28] and HQC.[29] Liew (2004) argues that where the sample is relatively large, such as 120 and above observations, HQC produces the most efficient results. I found, however, that use of this criterion resulted in cases of autocorrelation in some of the mean and variance equation residuals. As there were no such issues found when the AIC was used (see Appendix Table A5.3) it was decided that this criterion should provide the basis of the modelling undertaken.

[27] Akaike information criterion. See Burnham and Anderson (2004).
[28] Bayesian information criterion. See Burnham and Anderson (2004).
[29] Hannan Quinn Criterion. See Sin and White (1996).

Table 5.1: Optimal lags identified by HQC and AIC lag selection criteria

Countries	HQC	AIC
Botswana	11	17
Côte d'Ivoire	10	16
Egypt	16	20
Mauritius	9	14
Morocco	9	13
Namibia	10	14
Nigeria	11	16
South Africa	11	15
Tunisia	9	19
Zambia	11	15
Developed markets		
Canada	10	16
France	11	17
Germany	12	20
Italy	11	20
Japan	9	19
Spain	11	17
United Kingdom	11	18
Other markets		
China	11	20
India	9	20

It can be noted in Table 5.1 above that the AIC-based optimal lags were considerably longer than the HQC-based lags across all 19 countries. They are also considerably longer than the five lags used by Forbes and Rigobon (2002). This is possibly to be expected given that the static-correlation-based contagion tests do not need to take into consideration the issue of autocorrelation in mean and variance equations. The mean equations are presented in Appendix Tables A5.1. 1f identify that that the lagged values showed considerable statistical significance. For example, it can be noted that in respect to the pair of US and France, the US returns equation showed significance (at 1% and 10%, respectively) up to lag 11 in respect to both countries.

5.3.3 Development of the variance equations

The variance equations developed are presented in Tables A5.2a, A5.2c and A5.2e. For all 19 equation pairs modelled, they take the form of GARCH (1, 1).

Different GARCH specifications can be considered in respect to possible asymmetry in the data set associated with the tendency for bear phases of the market cycle to show a quicker pace of price adjustment than that found in bull phases.

It is possible to test for the most efficient functional form using information criteria in the same way in which the mean equations were tested.[30] Models can be tested as part of the set of GARCH models identified by Hentschel (1995) and subsequently described by Ghalanos (2013) as the family GARCH (fGARCH) model. Potential alternative specifications include:

- GJRGARCH model (Glosten, Jagannathan and Runkle 1993);
- Threshold GARCH (TGARCH) model (Zakoian 1994);
- Nonlinear ARCH (NGARCH) model (Higgins and Bera 1992);
- Nonlinear Asymmetric GARCH (NAGARCH) model (Engle and Ng 1993);

Despite the range of alternative asymmetric GARCH models available to us, it was found that none of the alternatives tested proved to be significantly superior to the standard GARCH (1, 1) specification. These alternative models were tested using information criteria; specifically, none of the alternatives were found to show superior performance to the standard GARCH (1, 1) model. I therefore applied the standard model for all of the 19 model pairs run. This conclusion is drawn from the information criteria test carried out on all the sampled markets. The results can be seen in Appendix

[30] It can be noted that in this case information criteria are estimated in relation to the likelihood function as estimation used Maximum Likelihood estimation as opposed to the Ordinary Least Squares used in the mean equations.

Tables A5.1 andA5.2. It can be noted from the tables that all three parameters of these models ($\alpha_{0,}$ $\alpha_{1,}$ β_1) were statistically significant in respect to the US at the 10% level (with most being significant at 5% or lower). The statistical significance across all three parameters was also high in respect to most of the developed markets, although the picture was a little more mixed in respect to the African markets (there were still considerable levels of significance found in respect to a number of the African countries).

Attempts were made towards other GARCH models on the African markets (Nigeria, Zambia, Tunisia and Mauritius) which showed insignificant alpha in there DCC equation using GARCH (1, 1) but the models returned lack of convergence across the different alternative GARCH models.

5.3.4 Autocorrelation testing in the mean and variance equations

As noted above, Tsay (2005) identified that where the mean and variance equations contain autocorrelations the robustness of the modelling process has to be called into question. We therefore performed a series of tests to check for autocorrelation in the models identified in the appendix. These are presented in Table A5.3. We perform the series of tests for robustness purposes given that the results from individual tests can sometime contradict each other; this is because they control for the influence of a specific lag-length in slightly different ways.

The tests employed are the Q-Statistic (Ljung and Box 1978) for the standardised residuals and standardised squared residuals. These are on the mean and variance equations, respectively, and are undertaken with lags of 5, 10, 20 and 50. The tests are joint tests with the null hypothesis stating that the parameter values on respective lags are simultaneously zero. Rejection of the null indicates the presence of misspecification errors (i.e. autocorrelation).

The Q-Statistic test on the squared standardised residuals was used to examine for the presence of ARCH effects in the variance equation also undertaken with the same number of lags. Hosking's (1980) multivariate portmanteau test statistics are also employed, along with the Li and McLeod (1981) multivariate tests. These are testing for simultaneous zero values across the respective mean and variance equations for both countries in the pair being tested at the time. The test results, presented in Appendices A5.3a to A5.5c, indicate that, with a few potential exceptions, the models I selected did not suffer from any autocorrelation issue (there were no cases where the null was rejected for a given pair across all the different test sets undertaken).

5.3.5 Test for financial crisis contagion: the equality of means test

Given that the conditional correlation is estimated across each point in time of the sample, the impact of financial crisis on the conditional correlation is examined using comparison-of-means tests. The test identifies the extent of the statistical significance of any differences in the mean daily conditional correlation in the pre-crisis period against the mean daily conditional correlation in the crisis period (multiple tests are undertaken using a fixed pre-crisis period of 01/01/2007–14/09/2008 and tested against a series of short sub-crisis periods).

The test undertaken is an *independent samples t-test*. Given that market volatility is normally expected to be greater during crisis periods it is expected that the variance of the pre-crisis and crisis period observations may differ. Differing forms of the t-test can be run on the basis of (i) equal variance samples and (ii) unequal variance samples. A

Levine test for variance equality (where the null hypothesis is variance equality) is therefore run to determine which test to apply. The effective difference between the two tests is that if unequal variances are identified the test becomes marginally stricter.

The null hypothesis is that mean daily correlations during the crisis is less than or equal to the pre-crisis period. If the null is rejected contagion is deemed to have been found.

$H_O : y2 \ \leq y1$ (absence of financial contagion)

$H_1 : y2 > \ y1$ (financial contagion)

$where \ y2 \ and \ y1$ are the mean daily correlation values between countries i and j during the crisis and pre-crisis periods respectively.

If equal variances are assumed the pooled variance t-test may be used. This is estimated as:

$$t = \frac{y2 - y1}{s_{pool}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(n_1 + n_2 - 2) \qquad (5.7)$$

$$where \ s_{pool}^2 = \frac{\sum(y_{1i} - \bar{y}_1)^2 + \sum\left(y_{2j} - \bar{y}_2\right)^2}{n_1 + n_2 - 2} = \frac{(n_1 - 1)s_1^2 + \ (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$$

n_1 – pre-crisis sample size

n_2 – during crisis sample size

If unequal variances are assumed the t-test is estimated as:

$$t = \frac{y2 - y1}{s_{pool}\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t(\ df_{satterthwaite}\ ) \qquad (5.8)$$

$$where \ df_{Satterrthwaite} = \frac{(n_1 - 1)(n_2 - 1)}{(n_1 - 1)(1 - c)^2 + \ (n_2 - 1)c^2} \ and \ c = \frac{s_1^2/n_1}{s_1^2/n_1 + s_2^2/n_2}$$

and s^2 is the variance. The Satterthwaite approximation was introduced by Satterthwaite (1946).

5.3.6 Financial contagion robustness test

To add to the robustness of the analysis, an alternative regression-based test is also undertaken to act as a confirmatory test. This takes the form of a test of significance in respect to a regression dummy variable representing the crisis periods.

$$C_{ij,t} = \mu_j + \delta_j Crisis\ DUMMY_t + \varepsilon_{ij,t} \qquad (5.9)$$

$where$ $C_{ij,t}$ is the conditional correlation at time t, between the US (i) and the second country (j). *Crisis* $DUMMY_t$ is a dummy variable taking on a value of 1 over the respective crisis period being tested. A *positive AND statistically significant* parameter value in respect to *Crisis DUMMY* is an indication that financial contagion has occurred. The hypothesis tested is:

$H_O : \delta_j \leq 0$ (absence of financial contagion)

$H_1 : \delta_j > 0$ (financial contagion)

It may be noted that a statistically significant negative parameter on the dummy variable would indicate a significant fall in correlation during the crisis period and does not constitute contagion. The test statistic is estimated as:

$$t = \frac{\widehat{\delta_j} - 0}{standard\ error(\widehat{\delta_j})} \qquad (5.10)$$

5.4 RESULTS

This section will start with a graphical presentation of the *daily* time-varying conditional correlations before using the comparison-of-means tests to identify financial contagion. This is done because the use of mean values can often obscure considerable spikes in conditional correlation over time. As well as presenting the correlations, the graphical analysis also shows the conditional covariance along with the conditional variances. This is done to examine why correlations change (see Equation 5.1 in respect to how correlations are estimated).

5.4.1 Time-varying conditional correlations: a stylised fact-based graphical descriptive analysis

Graphical presentations of the conditional correlation, conditional variances, ratio of conditional variances and covariance for each pair of country with the US are presented in this chapter's appendix (Section 5.7). Figures A5.1 to A5.10 are in respect to the African markets and Figures A5.11 to A5.19 are in respect to the developed markets and other markets (China and India). Each figure contains four sub-elements: the conditional correlation (top left); the conditional variances (top right); the conditional covariance (bottom right) and the ratio of the conditional variances (US/second country, bottom left).

The conditional correlation charts show that the US stock market is generally more highly correlated with the developed markets than African emerging and frontier markets. For example, in respect to Botswana the correlation with the US ranged between −0.11 and 0.12 over the period 2007-2009. For Canada, the correlation with the US ranged between 0.48 and 0.93 over this period, although it is clear that there were considerable spikes in the correlations associated with the onset of the crisis in the developed markets. The impact of the crisis on African markets was, however, mixed. The reaction of the conditional correlation to the financial crisis of some African countries shows negative values before the onset of the crisis. For instance, the correlations in Botswana, Côte d'Ivoire, and Morocco were largely negative. These values increased immediately after 15/09/2008 (Lehman's crisis) and fell back sometime in early 2009. This, in essence, supports my hypothesis of a short-term contagion effect.

For some developed markets, there was an initial fall in correlation in September 2008 after Lehman's. For example, conditional correlation charts of Canada, the UK, France and Italy showed a decline at the onset of the crisis (Lehman's announcement).This indicates that these markets responded relatively slowly to the initial falls in the US market or they are studying the US market closely and tried avoiding the effect of the crisis.

Changes in the conditional correlation are driven by changes in the ratio of the covariance to the product of the two market variances (see Equation 5.1). The covariance spiked around the period of the crisis in the developed markets and also in a number of the African markets. For example, in Canada it increased by more than four times the size. The correlation is only going to increase if the covariance increases proportionally more than does the product of the two variances. What my analysis shows is that changes in correlations were affected to a considerable degree by changes in the *relative* variances of the US and the second country.

Generally, changes in correlation tend to be driven by changes in the covariance. If markets in two countries move in the same direction then this will increase (i.e. it is positive). In times of financial crisis any contagion effect will result in considerable increases in this covariance. The covariance chart in Figure A5.1 (bottom right quadrant) shows an initial negative relationship between Botswana and the US. However, this suddenly shoots upward towards the end of 2008 and stays positive for some time in 2009 before dropping down. This gives a clear indication that the US crisis had a considerable negative impact on the Botswana market. Similar behaviour is exhibited in Morocco, Egypt, Mauritius, Namibia, Nigeria, South Africa and Tunisia; their covariances with the US are initially quite low but mostly moved in a positive direction (some shooting up drastically) during the crisis. These increases provide expectation of correlation increases during crisis. A cursory inspection of the developed markets also identifies that the covariance with the US increased significantly during the crisis.

The variances of the respective countries are shown in the top right quadrants of each figure, with the US in red and the second country in blue. It is immediately evident from these charts that the US is more volatile than Botswana, Morocco, Namibia, South Africa and Tunisia during the crisis period (towards the end of 2008). This suggests that the impact on African markets was considerably smaller over this period. As the crisis began in the US, the increase in US variance is expected. Although the change in African markets was generally smaller there were some considerable spikes. Mauritius, for instance, shows many spikes throughout the sample period and it is especially higher than the US at some point after the onset of the crisis. South Africa’s variances, even though lower than the US, show appreciable reaction during the crisis period. It can be noted that these spikes could also possibly reflect African issues rather than being related to the US crisis. Africa is a continent where there are considerable political upheavals. African markets may have been responding to local and regional issues over what was a considerable period of time.

The situation is different for developed markets – there is also clear evidence of high volatility in the conditional variance of this group. Canada in particular displayed what could be seen as an almost identical movement in conditional variances with the US throughout the sample period. The remaining developed markets, including Japan, shows the crisis affected their conditional variance; there was clear upward movement during the crisis period. The story is different for the non-African emerging markets sampled: China and India. Here the conditional variance of China is higher than that of the US till around late 2008 (the crisis period), when it begins to fall. This suggests that the initial phase of the crisis had very little impact on China.

As noted in the introduction to this section, the ratio of the conditional variances (ratio of US/second country, bottom left quadrant of the figures) showed considerable differences over the crisis period. In most of the African markets this ratio rose around the period of the financial crisis. This indicates that, in general, African markets responded to a lesser degree than their US counterpart. In respect to developed markets there was some evidence to suggest that the ratio was relatively stable. This suggests that other developed markets experienced similar levels of volatility as their US counterpart. Interestingly, the ratio seems to fall in some cases, for example, the UK, Italy, Spain and China, indicating that the impact was considerably *more* than it was on the US even though the crisis had US origins. The UK is interesting; an initial spike in the ratio when the crisis began, indicating an initially higher impact on the US, was replaced by a considerable fall, indicating that the crisis had a much larger medium-term impact on UK markets than US markets.

In conclusion to this section, I would say that considerable care needs to be taken when interpreting correlations data as the impact of the crisis on the covariance can be in part, masked (or even increased) by the impact of changes in relative market volatilities over the period. This appears to be especially important in respect to developed markets where, in some cases, higher relative levels of US volatility at the start of the crisis gave way to lower relative levels of US volatility as the crisis developed.

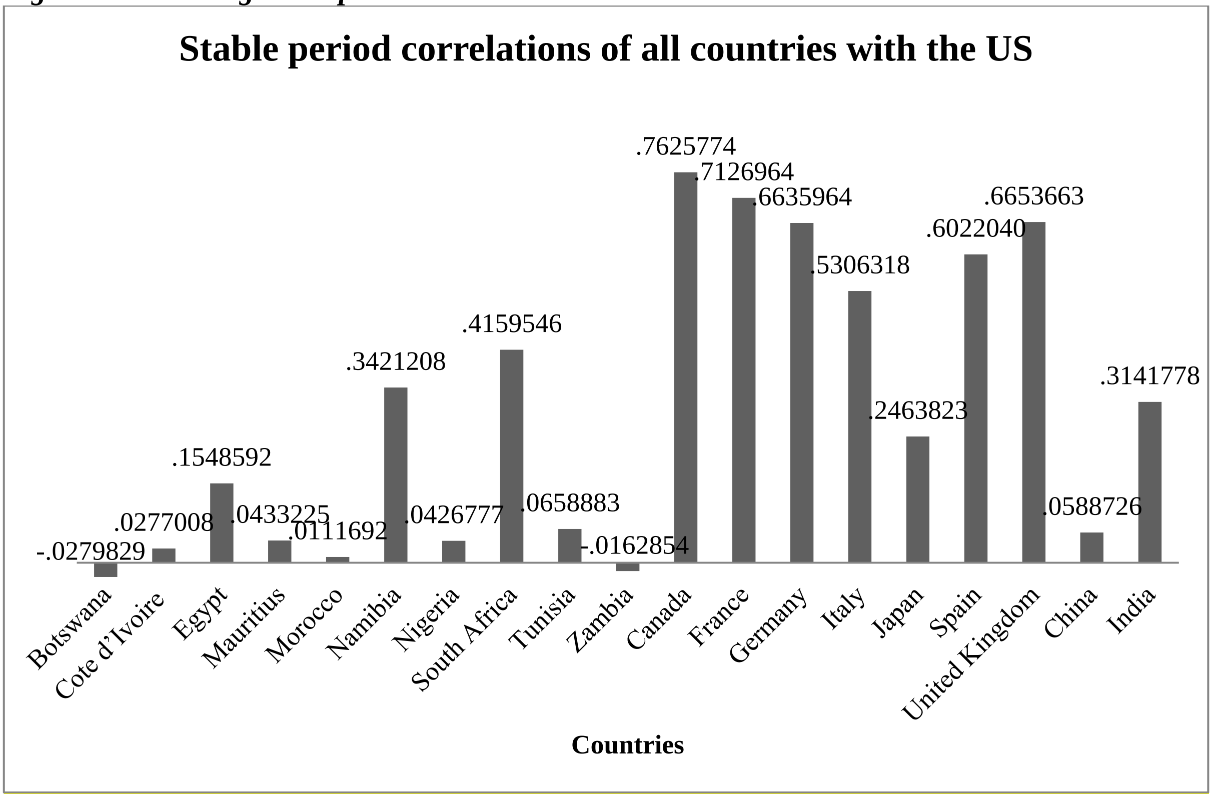
5.4.2 Time-varying mean correlations: a stylised fact-based descriptive analysis

As has been discussed above, there were considerable variations in the conditional correlations over time. It also appears from the charts that the correlations were higher during the crisis period than the pre-crisis period. However, in order to undertake formal hypothesis tests for contagion I undertake statistical comparison-of-mean tests between the two periods. Before I undertake a statistical test for contagion in Section 5.4.3, I will undertake a descriptive analysis of the means. This section will attempt to identify the changes in mean correlations during the crisis using the identified periods under study. As a reminder, the periods under consideration are:

1. Long crisis period (15/09/2008-15/10/2009)
2. Sub-period 1 (15/09/2008-10/10/2008)
3. Sub-period 2 (15/09/2008-17/10/2008)
4. Sub-period 3 (15/09/2008-27/10/2008)
5. Sub-period 4 (15/09/2008-20/11/2008)

Correlations of all countries with the US during the pre-crisis and crisis periods are used to plots charts in order to adequately visualise the differences in the relationship of the countries with the US before and during crisis. Figure 5.1 below gives the correlations of all sample countries with the US during the period of tranquillity. As the stable period remains constant throughout my analysis, only one chart is used to present this period. It is immediately evident from Figure 5.1 that all the African markets have a less than 50% correlation with the US. The most correlated market with the US in this region is South Africa with 41%. Namibia has about 30% correlation with the US while Botswana and Zambia produced negative correlation values of −0.028 and −0.016 during the tranquil period. The smallest correlation value is produced between the US and Botswana (*US and Botswana is also the smallest correlation in the previous chapter).* The negative correlations indicate movement in opposite directions; therefore, a sudden increase in correlation during the crisis could lead to a contagion effect.

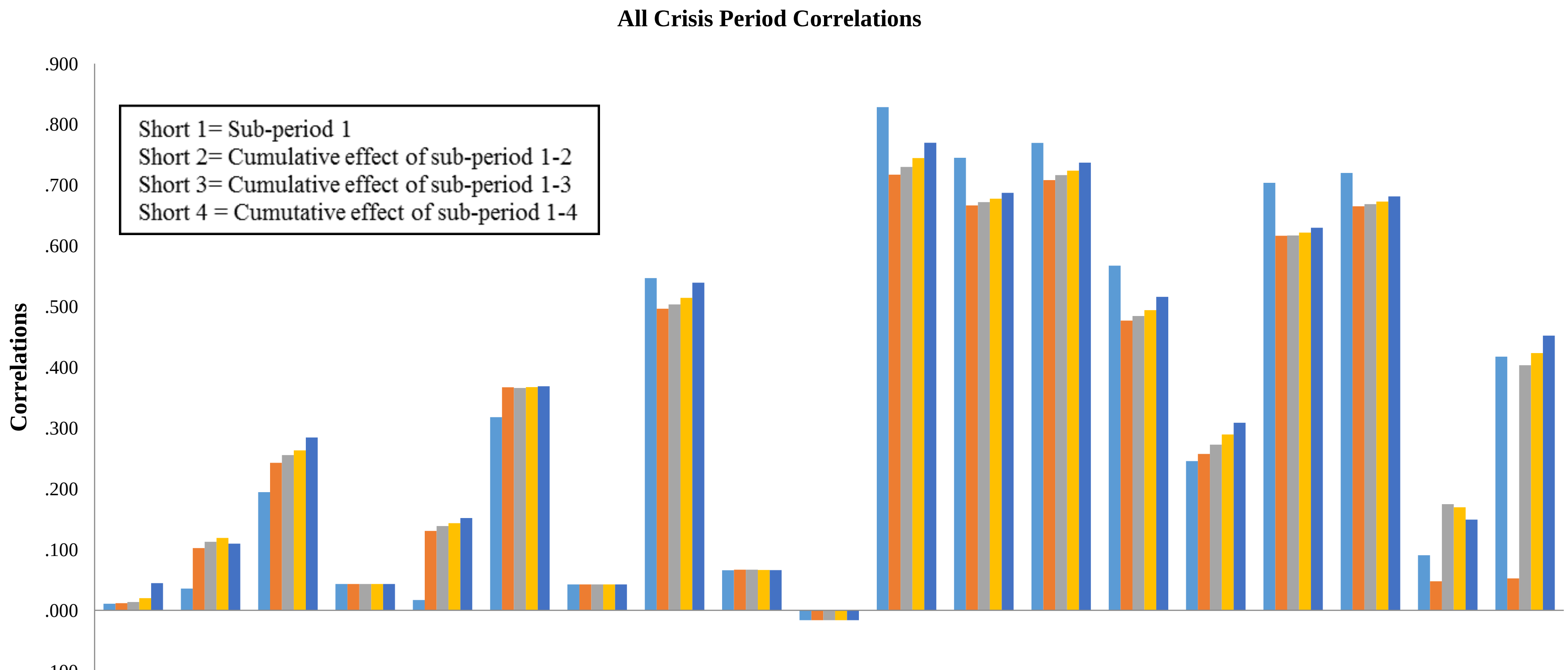
Figure 5.1: Showing stable period correlations



But, more interestingly, if we look at the connections of South Africa to the US, it is evident that this market is more connected with the US than other African markets. Therefore, South Africa could act as a propagation mechanism in Africa. Consequently, any shock originating in the US stock market could hit instantly the South African stock market, either as contagion or interdependence that would act as a transmitter to the rest of the African markets.

For the developed markets, Canada provided the highest correlation value with the US at 76%. France, Germany, Italy, Spain and the UK all had above 50% correlation with the US before the crisis. Japan is the only developed market in the sample to have a less than 50% correlation (25%) during tranquillity. The comparative markets (China and India) provided positive correlation but India did better at 31% whereas China had only 0.589%. As stated in the methodology section, the crisis period had sub-elements in which peaks are identified using the VIX. Therefore, correlations for the long crisis and the four identified peaks are used to plot Figure 5.2 below.

Figure 5.2: Showing crisis period correlations



	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
long	.0108817	.0358839	.1944376	.0433226	.0168558	.3180376	.0426777	.5468666	.0660145	-.016285	.8283888	.7449817	.7694720	.5674647	.2455765	.7038020	.7198560	.0907693	.4175565
short 1	.0116971	.1025270	.2427418	.0433225	.1308204	.3671186	.0426777	.4963532	.0668851	-.016285	.7170734	.6664872	.7082006	.4769963	.2573353	.6166037	.6649986	.0479118	.0524466
short 2	.0136816	.1127702	.2554831	.0433226	.1386932	.3659704	.0426777	.5035673	.0668608	-.016285	.7298377	.6718843	.7163823	.4844658	.2727989	.6171340	.6685909	.1747277	.4033911
short 3	.0201280	.1192317	.2632762	.0433226	.1435071	.3674708	.0426777	.5144670	.0664243	-.016285	.7444916	.6776201	.7236939	.4942101	.2895384	.6218099	.6728302	.1696668	.4234136
short 4	.0448440	.1097698	.2843801	.0433226	.1518059	.3687399	.0426777	.5393864	.0662304	-.016285	.7696109	.6872395	.7369421	.5160244	.3086694	.6296625	.6813967	.1494005	.4522964

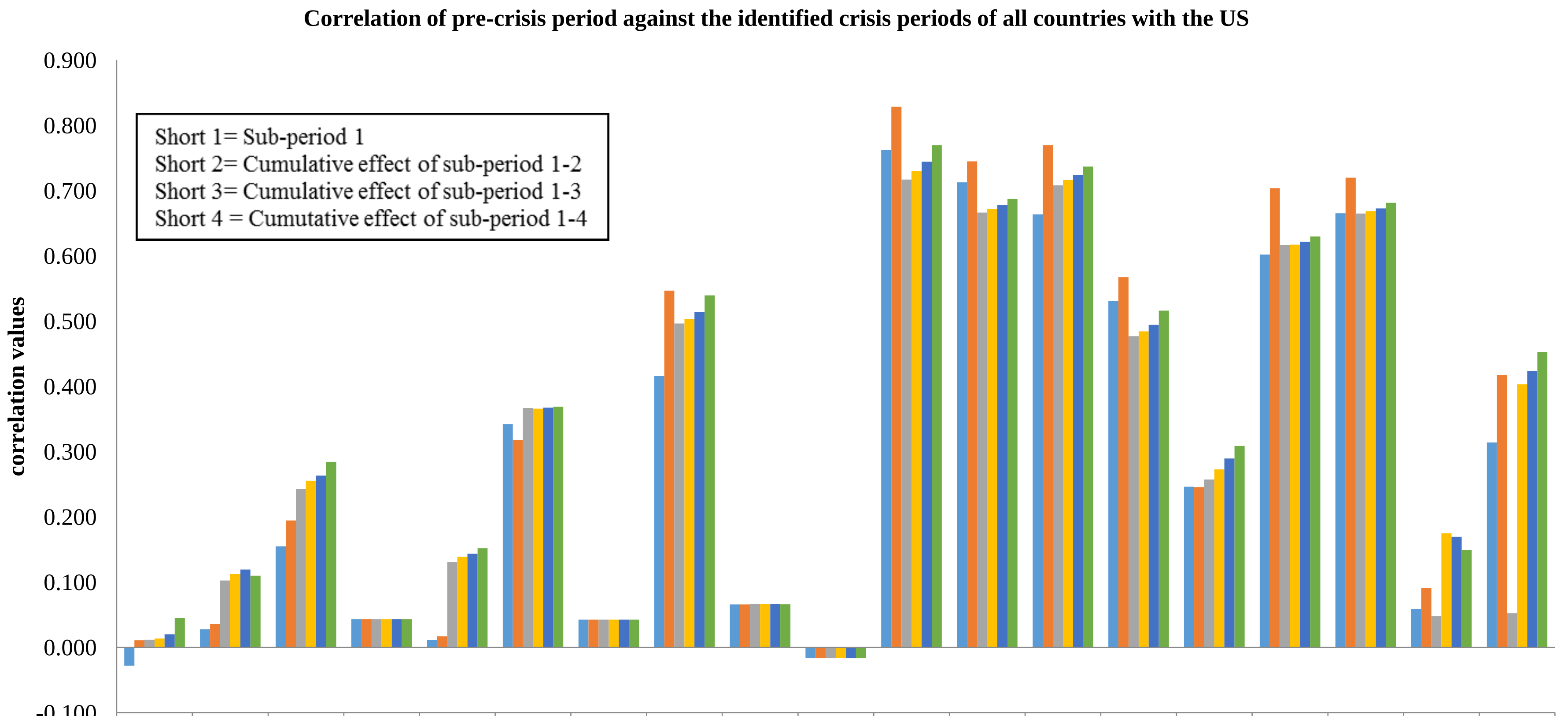
Countries

As indicated in the chart above, the highest correlation during the long crisis period in Africa is produced in South Africa at about 55%. Zambia is the only African country with negative correlation throughout the different crisis periods. Also, the correlations of Zambia, Nigeria and Mauritius remained unchanged throughout the crisis periods. While that of Tunisia showed negligible variation, it could also be referred to as unchanged. This could be resulting from the insignificant alpha in the DCC equation. Botswana, Egypt, Morocco and Namibia have their highest correlation from the cumulative impact of sub-period 1-4. Only South Africa has the highest correlation during the long crisis period in the African markets under study. India's highest correlation is also from the *cumulative* impact of periods 1 to 4 (sub-period 4), as with most African markets.

All developed markets excluding Japan have their highest correlation during the long crisis period. The highest correlation (83%) of the sampled markets is produced in the long crisis period in Canada.

In order to appreciate the change in correlation during the crisis, I plotted a bar chart of the stable period with all crisis periods presented in Figure 5.3.

Figure 5.3: Showing stable period (pre-crisis period) correlations against all crisis period correlations



	BWA	CIV	EGY	MUS	MAR	NAM	NGA	SA	TUN	ZMB	CAN	FRA	GER	ITA	JPN	SPN	U K	CHN	IND
Pre-crisis	-0.02798	0.02770	0.15486	0.04332	0.01117	0.34212	0.04268	0.41595	0.06589	-0.01629	0.76258	0.71270	0.66360	0.53063	0.24638	0.60220	0.66537	0.05887	0.31418
Long	.0108817	.0358839	.1944376	.0433226	.0168558	.3180376	.0426777	.5468666	.0660145	-.016285	.8283888	.7449817	.7694720	.5674647	.2455765	.7038020	.7198560	.0907693	.4175565
Short 1	.0116971	.1025270	.2427418	.0433225	.1308204	.3671186	.0426777	.4963532	.0668851	-.016285	.7170734	.6664872	.7082006	.4769963	.2573353	.6166037	.6649986	.0479118	.0524466
Short 2	.0136816	.1127702	.2554831	.0433226	.1386932	.3659704	.0426777	.5035673	.0668608	-.016285	.7298377	.6718843	.7163823	.4844658	.2727989	.6171340	.6685909	.1747277	.4033911
Short 3	.0201280	.1192317	.2632762	.0433226	.1435071	.3674708	.0426777	.5144670	.0664243	-.016285	.7444916	.6776201	.7236939	.4942101	.2895384	.6218099	.6728302	.1696668	.4234136
Short 4	.0448440	.1097698	.2843801	.0433226	.1518059	.3687399	.0426777	.5393864	.0662304	-.016285	.7696109	.6872395	.7369421	.5160244	.3086694	.6296625	.6813967	.1494005	.4522964

Countries

It is immediately evident from the figure above that the long crisis period correlations surpasses all other crisis correlations, including the stable period correlations in South Africa, Canada, France, Germany, Italy, Spain and the UK. This leads to the expectation of a contagion effect if the long crisis period is measured against the stable period. The only negative correlation found in Botswana is during the stable period. Zambia has negative correlation in all periods, including the stable period.

The most striking changes in correlation are evident in India. Here, the correlation of the long crisis period is also higher than the stable period, but when the stable period is compared to sub-period 1, the correlation reduced from 0.314 to 0.0524 and increased sharply from the cumulative impact of sub-period 1-2 to 0.4033. India's correlation with the US further increased in sub-periods 1-3 (0.4234) and 1- 4 (0.4522). When compared to the crisis periods in African markets, the stable period correlation is lower than all the crisis periods in Botswana, Côte d'Ivoire, Egypt, Morocco and South Africa, as expected. This, however, does not signify that a contagion effect will be found in these countries. Even in the developed markets where correlations are high (above 70%), one needs to take into account whether the presence of a high degree of correlations is sufficient proof of contagion. If markets are historically cross-correlated (e.g. most developed markets in this research with the US), then a sharp change in one market will have an expected change in given magnitude in the other markets. If there is no significant increase in correlations during the crisis period, then the markets are simply reacting (interdependencies) to each other, as dictated by their traditional relationship. The scenario is quite different if the correlations change substantially subsequent to the onset of the crises, in which case one can indeed make the case for contagion (such as the situation seen in India). The significance or otherwise of the increased correlations discussed in this section are discussed in the following section.

5.4.3 Time-varying mean correlations: a comparison-of-means statistical test for contagion

This section answers the principal hypothesis set out in this thesis that contagion occurred from the US to developed and African markets during the 2007-09 financial crisis.

Estimates are based on different observations for every combination of country with the US. A contagion test is carried out on the long period (Hypothesis 1) and the four sub-periods (Hypothesis 2), as was undertaken in respect to the constant correlation analysis (Chapter 4). Tables 5.2 to 5.6 present the results for the tests of contagion. The test undertaken is a one-tail comparison-of-means test of the form indicated in Section 5.3.5 above.

The t- tests for the presence of contagion are based on one-tail tests at 5%. A ‘Yes’ in the last column indicates evidence of contagion, while a ‘No’ indicates no contagion. Where markets exhibit high correlations in their traditional relationship and do not reject the null of no contagion, we interpret this as *interdependence (increase in correlation that is not statistically significant at 5%)*. In this thesis, a correlation of 40% and above before the crisis period must be found in the markets to support the theory of interdependencies during crisis.

5.4.3.1 Hypothesis 1: Long crisis period contagion effects

Table 5.2 below presents a contagion test on the long crisis period. Evidence of contagion (defined as a statistically significant increase in correlation at 5%) in African markets is found in Botswana, Côte d'Ivoire, Egypt, Mauritius and South Africa.

Increases in correlation that were not statistically significant at 5% were found in respect to Morocco, Nigeria and Tunisia. This is not termed as interdependence due to initial low correlations during period of tranquillity. Reductions in correlation are found in Namibia and Zambia.

Evidence of contagion is found in all developed markets and "other" emerging markets, with the exception of Japan. In the case of Japan, the mean correlation was marginally lower (fourth decimal place) during the crisis period.

Table 5.2: Comparison-of-means tests for the long period

African markets	Stable period		Crisis period		Test for equality of variances[1]		T-test for equality of means[2,3]	Evidence of contagion[4]
	Mean	Standard deviation	*Mean*	Standard deviation	*F*	Sig		
Botswana	-0.028	0.035	0.011	0.043	30.776	0.000	**12.060*** **	**YES**
Côte d'Ivoire	0.028	0.035	0.036	0.074	187.983	0.000	**1.659** **	**YES**
Egypt	0.155	0.066	0.194	0.076	14.616	0.000	**5.991*** **	**YES**
Mauritius	0.043	0.000	0.043	0.000	24.590	0.000	**1.881** **	**YES**
Morocco	0.011	0.036	0.017	0.081	159.192	0.000	1.060	NO
Namibia	0.342	0.217	0.318	0.093	164.047	0.000	-1.965	NO
Nigeria	0.043	0.000	0.043	0.000	4.982	0.026	0.904	NO
South Africa	0.416	0.144	0.547	0.043	214.195	0.000	**17.040*** **	**YES**
Tunisia	0.066	0.002	0.066	0.002	1.811	0.179	0.935	NO
Zambia	-0.016	0.000	-0.016	0.000	8.478	0.004	-1.269	NO
Developed markets								
Canada	0.763	0.112	0.828	0.046	121.101	0.000	**10.486*** **	**YES**
France	0.713	0.053	0.745	0.053	4.051	0.045	**7.795*** **	**YES**
Germany	0.664	0.059	0.769	0.030	67.056	0.000	**30.620*** **	**YES**
Italy	0.531	0.101	0.567	0.052	123.984	0.000	**6.169*** **	**YES**
Japan	0.246	0.050	0.246	0.067	24.805	0.000	-0.164	NO
Spain	0.602	0.065	0.704	0.046	34.937	0.000	**23.574*** **	**YES**
United Kingdom	0.665	0.033	0.720	0.028	3.672	0.056	**22.150*** **	**YES**
Other markets								
China	0.059	0.048	0.091	0.057	9.078	0.003	**7.340*** **	**YES**
India	0.314	0.052	0.418	0.054	0.020	0.887	**24.200*** **	**YES**

[1] Levine's test of variance equality; where rejection of the null hypothesis indicates inequality. [2] The *t*-value reported is the form appropriate for the variance identified. [3] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [4] Contagion is defined as statistical significance at 5% level.

5.4.3.2 Hypothesis 2: Short crisis periods contagion effects

The first sub-period (15/09/2008-10/10/2008), from Lehman's announcement to the first spike identified by the VIX, presented contagion in Botswana, Côte d'Ivoire, Egypt, Morocco, Namibia and South Africa. Evidence of contagion was not found in Mauritius, Nigeria, Tunisia and Zambia at the onset of the crisis. The four African markets that showed no contagion effect are those that had an insignificant alpha in the DCC-MGARCH model (see Section 5.3 above for details). Therefore this result is not unexpected.

It is noticeable from Table 5.3 that the highly correlated market with the US actually had a reduction in correlation at the onset of the crisis. This includes Canada, France, Italy and the UK. Germany and Spain are the only developed markets to exhibit contagion effect in sub-period 1. The comparative markets, China and India, both showed evidence of contagion with China being the most affected of all markets. The result for China is not surprising due to the high business relationship between China and the US.

Table 5.3: Comparison-of-means test for sub-period 1

African markets	Stable period		Crisis period		Test for equality of variances[1]		T-test for equality of means[2,3]	Evidence of contagion[4]
	Mean	Standard deviation	*Mean*	Standard deviation	*F*	Sig		
Botswana	-0.028	0.035	0.012	0.045	1.873	0.172	**4.697*****	**YES**
Côte d'Ivoire	0.028	0.035	0.103	0.013	14.658	0.000	**21.56*****	**YES**
Egypt	0.155	0.066	0.243	0.059	0.801	0.371	**4.71*****	**YES**
Mauritius	0.043	0.000	0.043	0.000	1.068	0.302	0.229	NO
Morocco	0.011	0.036	0.131	0.030	1.037	0.309	**13.85*****	**YES**
Namibia	0.342	0.217	0.367	0.037	29.933	0.000	**1.839****	**YES**
Nigeria	0.043	0.000	0.043	0.000	4.516	0.034	1.312*	NO
South Africa	0.416	0.144	0.496	0.058	9.357	0.002	**5.342*****	**YES**
Tunisia	0.066	0.002	0.067	0.004	45.408	0.000	1.017	NO
Zambia	-0.016	0.000	-0.016	0.000	0.204	0.652	0.225	NO
Developed markets								
Canada	0.763	0.112	0.717	0.049	7.150	0.008	-3.676	NO
France	0.713	0.053	0.666	0.015	19.087	0.000	-10.962	NO
Germany	0.664	0.059	0.708	0.020	11.163	0.001	**8.195*****	**YES**
Italy	0.531	0.101	0.477	0.026	28.042	0.000	-6.935	NO
Japan	0.246	0.050	0.257	0.029	5.618	0.018	1.52*	NO
Spain	0.602	0.065	0.617	0.020	22.139	0.000	**2.622*****	**YES**
United Kingdom	0.665	0.033	0.665	0.013	9.615	0.002	-0.111	NO
Other markets								
China	0.059	0.048	0.176	0.049	0.023	0.880	**8.978*****	**YES**
India	0.314	0.052	0.378	0.058	0.007	0.934	**5.004*****	**YES**

[1] Levine's test of variance equality; where rejection of the null hypothesis indicates inequality. [2] The t-value reported is the form appropriate for the variance identified. [3] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [4] Contagion is defined as statistical significance at 5% level.

Table 5.4 below showed that the cumulative impact of sub-period 1-2 provided higher correlations than the stable period correlations in Botswana, Côte d'Ivoire, Egypt, Morocco, Namibia and South Africa. As such, contagion is expected. The contagion tests follow suit, showing contamination in these countries. Tunisia and Zambia remain uncontaminated in sub-period 1-2.

Germany appears to be the most affected developed market with a t-statistic of 9.10***. Japan and Spain also showed evidence of contagion while Canada, France, Italy and the UK had no evidence of contagion. Interdependence (defined as an increase in correlation that is not statistically significant at 5%) is evident in the UK alone. China and India are also contaminated but the most affected of all countries is, surprisingly, Morocco with a t-statistic of 16.55***.

Table 5.4: Cumulative Comparison-of-means test on sub-period 1-2

African markets	Stable period		Crisis period		Test for equality of variances[1]		T-test for equality of means[2,3]	Evidence of contagion[4]
	Mean	Standard deviation	*Mean*	Standard deviation	*F*	Sig		
Botswana	-0.028	0.035	0.014	0.041	0.365	0.546	**5.449*** **	**YES**
Côte d'Ivoire	0.028	0.035	0.113	0.026	4.116	0.043	**15.02*** **	**YES**
Egypt	0.155	0.066	0.255	0.057	0.853	0.356	**6.147*** **	**YES**
Mauritius	0.043	0.000	0.043	0.000	27.534	0.000	**1.994** **	**YES**
Morocco	0.011	0.036	0.139	0.033	0.335	0.563	**16.55*** **	**YES**
Namibia	0.342	0.217	0.366	0.034	38.920	0.000	**1.863** **	**YES**
Nigeria	0.043	0.000	0.043	0.000	2.792	0.096	**2.198** **	**YES**
South Africa	0.416	0.144	0.504	0.053	13.851	0.000	**6.722*** **	**YES**
Tunisia	0.066	0.002	0.067	0.004	32.951	0.000	1.212	NO
Zambia	-0.016	0.000	-0.016	0.000	0.255	0.614	0.252	NO
Developed markets								
Canada	0.763	0.112	0.730	0.054	6.810	0.009	-2.655	NO
France	0.713	0.053	0.672	0.018	19.076	0.000	-9.231	NO
Germany	0.664	0.059	0.716	0.025	10.625	0.001	**9.107*** **	**YES**
Italy	0.531	0.101	0.484	0.029	30.755	0.000	-5.991	NO
Japan	0.246	0.050	0.273	0.044	0.202	0.653	**2.427*** **	**YES**
Spain	0.602	0.065	0.617	0.019	29.097	0.000	**3.008*** **	**YES**
United Kingdom	0.665	0.033	0.669	0.014	10.529	0.001	1.001	NO
Other markets								
China	0.059	0.048	0.175	0.042	0.694	0.405	**10.34*** **	**YES**
India	0.314	0.052	0.403	0.072	3.840	0.051	**7.75*** **	**YES**

[1] Levine's test of variance equality; where rejection of the null hypothesis indicates inequality. [2] The t-value reported is the form appropriate for the variance identified. [3] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [4] Contagion is defined as statistical significance at 5% level.

For the cumulative impact of sub-period 1-3, Tunisia and Zambia are the only African markets not affected. The most affected market is, once again, Morocco with a test statistic of 19.220***. This result is presented in Table 5.5 below.

Again, Canada, France and Italy show no evidence of contagion in sub-period 1-3. This time, the UK is affected along with Germany, Japan and Spain. China and India also show evidence of contagion effect.

Table 5.5: Cumulative comparison-of-means test on sub-period 1-3

African markets	**Stable period**		**Crisis period**		**Test for equality of variances[1]**		**T-test for equality of means[2,3]**	**Evidence of contagion[4]**
	Mean	**Standard deviation**	***Mean***	**Standard deviation**	***F***	**Sig**		
Botswana	-0.028	0.035	0.020	0.038	0.135	0.713	**7.067*** **	**YES**
Côte d'Ivoire	0.028	0.035	0.119	0.026	2.664	0.103	**13.610*** **	**YES**
Egypt	0.155	0.066	0.263	0.054	1.856	0.174	**7.346*** **	**YES**
Mauritius	0.043	0.000	0.043	0.000	28.178	0.000	**2.806*** **	**YES**
Morocco	0.011	0.036	0.144	0.031	0.796	0.373	**19.220*** **	**YES**
Namibia	0.342	0.217	0.367	0.031	50.724	0.000	**2.083** **	**YES**
Nigeria	0.043	0.000	0.043	0.000	1.774	0.184	**1.719** **	**YES**
South Africa	0.416	0.144	0.514	0.052	18.530	0.000	**8.221*** **	**YES**
Tunisia	0.066	0.002	0.066	0.003	24.734	0.000	0.849	NO
Zambia	-0.016	0.000	-0.016	0.000	0.305	0.581	0.276	NO
Developed markets								
Canada	0.763	0.112	0.744	0.056	7.863	0.005	-1.541	NO
France	0.713	0.053	0.678	0.020	18.902	0.000	-7.912	NO
Germany	0.664	0.059	0.724	0.027	10.755	0.001	**10.600*** **	**YES**
Italy	0.531	0.101	0.494	0.033	32.402	0.000	-4.670	NO
Japan	0.246	0.050	0.290	0.050	1.019	0.313	**4.409*** **	**YES**
Spain	0.602	0.065	0.622	0.020	35.855	0.000	**4.080*** **	**YES**
United Kingdom	0.665	0.033	0.673	0.015	11.480	0.001	**2.338*** **	**YES**
Other markets								
China	0.059	0.048	0.170	0.038	2.369	0.125	**11.330*** **	**YES**
India	0.314	0.052	0.423	0.075	8.539	0.004	**7.712*** **	**YES**

[1] Levine's test of variance equality; where rejection of the null hypothesis indicates inequality. [2] The t-value reported is the form appropriate for the variance identified. [3] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [4] Contagion is defined as statistical significance at 5% level.

Again, the evidence from the cumulative impact of sub-period 1-4 (presented in Table 5.6 below) is showing that contagion has occurred in most African countries except Nigeria, Tunisia and Zambia.

For the developed markets, Italy is not affected while Germany, Japan, Spain and the UK show contagion effect. China and India show evidence of contagion, as they did in all crisis periods.

Interdependence is found in Canada and France, where mean correlations increased from 0.763 and 0.664 during tranquillity to 0.770 and 0.724 during the crisis. The most affected developed market is Germany with a t-value of 14.88*** while Morocco has the overall highest t-value of 25.290***. This result is presented in Table 5.6 below.

Table 5.6: Cumulative comparison-of-means test on sub-period 1-4

African markets	Stable period		Crisis period		Test for equality of variances[1]		T-test for equality of means[2,3]	Evidence of contagion[4]
	Mean	Standard deviation	*Mean*	Standard deviation	*F*	Sig		
Botswana	-0.028	0.035	0.045	0.043	3.639	0.057	**13.139*** **	**YES**
Côte d'Ivoire	0.028	0.035	0.110	0.025	6.383	0.012	**19.900*** **	**YES**
Egypt	0.155	0.066	0.284	0.049	7.510	0.006	**14.160*** **	**YES**
Mauritius	0.043	0.000	0.043	0.000	25.163	0.000	**3.813*** **	**YES**
Morocco	0.011	0.036	0.152	0.028	3.361	0.067	**25.290*** **	**YES**
Namibia	0.342	0.217	0.369	0.026	83.328	0.000	**2.3170** **	**YES**
Nigeria	0.043	0.000	0.043	0.000	7.327	0.007	0.354	NO
South Africa	0.416	0.144	0.539	0.053	32.720	0.000	**11.780*** **	**YES**
Tunisia	0.066	0.002	0.066	0.003	17.047	0.000	0.798	NO
Zambia	-0.016	0.000	-0.016	0.000	0.458	0.499	0.338	NO
Developed markets								
Canada	0.763	0.112	0.770	0.056	15.058	0.000	0.719	NO
France	0.664	0.059	0.724	0.027	29.705	0.000	-6.478	NO
Germany	0.664	0.059	0.737	0.028	13.773	0.000	**14.88*** **	**YES**
Italy	0.531	0.101	0.516	0.039	41.251	0.000	-1.939	NO
Japan	0.246	0.050	0.309	0.047	0.247	0.619	**7.955*** **	**YES**
Spain	0.602	0.065	0.630	0.019	60.084	0.000	**6.469*** **	**YES**
United Kingdom	0.665	0.033	0.681	0.017	15.570	0.000	**5.547*** **	**YES**
Other markets								
China	0.059	0.048	0.149	0.056	0.826	0.364	**11.550*** **	**YES**
India	0.314	0.052	0.452	0.072	11.799	0.001	**12.500*** **	**YES**

[1] Levine's test of variance equality; where rejection of the null hypothesis indicates inequality. [2] The t-value reported is the form appropriate for the variance identified. [3] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [4] Contagion is defined as statistical significance at 5% level.

5.4.4 Summary of findings

The findings of comparison-of-means tests are presented in Tables 5.2 to 5.6 above. The summarised results based on the long crisis period and the four sub-periods are presented in Table 5.6.1 below. This shows more contagion effect in Africa than found in Chapter 4.

Table 5.6.1: Evidence of contagion of the comparison-of–means Test

Countries	**Contagion?**				
African markets	**Long period**	**Sub-period 1**	**Sub-period 1-2**	**Sub-period 1-3**	**Sub-period 1-4**
Botswana	**YES**	**YES**	**YES**	**YES**	**YES**
Côte d'Ivoire	**YES**	**YES**	**YES**	**YES**	**YES**
Egypt	**YES**	**YES**	**YES**	**YES**	**YES**
Mauritius	**YES**	NO	**YES**	**YES**	**YES**
Morocco	NO	**YES**	**YES**	**YES**	**YES**
Namibia	NO	**YES**	**YES**	**YES**	**YES**
Nigeria	NO	NO	**YES**	**YES**	NO
South Africa	**YES**	**YES**	**YES**	**YES**	**YES**
Tunisia	NO	NO	NO	NO	NO
Zambia	NO	NO	NO	NO	NO
Developed markets					
Canada	**YES**	NO	NO	NO	NO
France	**YES**	NO	NO	NO	NO
Germany	**YES**	**YES**	**YES**	**YES**	**YES**
Italy	**YES**	NO	NO	NO	NO
Japan	NO	NO	**YES**	**YES**	**YES**
Spain	**YES**	**YES**	**YES**	**YES**	**YES**
United Kingdom	**YES**	NO	NO	**YES**	**YES**
Other markets					
China	**YES**	**YES**	**YES**	**YES**	**YES**
India	**YES**	**YES**	**YES**	**YES**	**YES**

Evidences to support the existence of interdependencies in the markets under study are found in:

- The UK from the cumulative impact of sub-period 1-2;
- Canada and France from the cumulative impact of sub-period 1-4.

These are the only markets that satisfied the notion of interdependence laid out in Section 5.4.3 above. An increase in correlation that is not statistically significant at 5% is found in respect to Morocco, Nigeria and Tunisia in the long crisis period. However, since their correlations with the US were low before the crisis, this result is simply identified as no contagion.

In conclusion to the comparison-of-means results, the findings of this section are inconsistent with those of the constant correlation analysis in Chapter 4. However the test applied in this chapter differs markedly: 1) I used a time-varying correlation analysis; 2) the crisis period is measured against the stable period (instead of full period against crisis period as in Forbes and Rigobon, 2002); and 3) the numbers of lags applied are also considerably longer than those of the constant correlation analysis.

5.5 CONTAGION ROBUSTNESS TESTING

I undertake a second set of tests for contagion using a regression-base dummy variable analysis. The details of the tests undertaken are described in Section 5.3.6 above. They are in the form of a one-tail test on a regression between the conditional correlation and a dummy variable that represents the crisis period. A statistically significant positive value for the dummy variable is an indication of financial contagion.

I repeat the contagion tests undertaken in Tables 5.2-5.6 above in respect to the long period and the various sub-periods using this dummy variable-based methodology. The results are shown below.

Long period

For the results to be considered robust, the conclusions drawn in Table 5.7 below should be the same as those in Table 5.2. This is what is found and therefore it can be concluded that the results are robust in respect to the two alternative methodologies applied.

Table 5.7: Dummy test for the long period

African markets	R squared	Coefficients			Evidence of contagion[2]
		Unstandardised coefficient		t	
		β			
		Constant	*Dummy*	*Dummy*[1]	
Botswana	0.199	-0.028	0.039	**12.642*****	**YES**
Côte d'Ivoire	0.005	0.028	0.008	**1.874****	**YES**
Egypt	0.071	0.155	0.040	**6.169*****	**YES**
Mauritius	0.006	0.043	0.000	**2.001****	**YES**
Morocco	0.002	0.011	0.006	1.221	NO
Namibia	0.004	0.342	-0.024	-1.710	NO
Nigeria	0.001	0.043	0.000	0.967	NO
South Africa	0.239	0.416	0.131	**14.392*****	**YES**
Tunisia	0.001	0.066	0.000	0.935	NO
Zambia	0.003	-0.016	0.000	-1.449	NO
Developed markets					
Canada	0.110	0.763	0.066	**9.090*****	**YES**
France	0.083	0.713	0.032	**7.795*****	**YES**
Germany	0.528	0.664	0.106	**27.332*****	**YES**
Italy	0.044	0.531	0.037	**5.523*****	**YES**
Japan	0.000	0.246	-0.001	-0.174	NO
Spain	0.421	0.602	0.102	**22.071*****	**YES**
United Kingdom	0.424	0.665	0.054	**22.154*****	**YES**
Other markets					
China	0.084	0.059	0.032	**7.601*****	**YES**
India	0.477	0.314	0.103	**24.200*****	**YES**

[1]*Significant at 10%, **Significant at 5%, ***Significant at 1%. [2] Contagion is defined as statistical significance at 5% level.

Short periods

There are some differences in respect to sub-period 1 between the comparison-of-means results and the dummy variable results. In respect to the African markets, the dummy variable tests in Table 5.8 below indicate contagion in respect to Nigeria and Tunisia (not found in Table 5.3 above). While the comparison-of-means test shows evidence of contagion in Namibia, the dummy test indicates no contagion.

There is also a difference in respect to the developed markets. For example, Spain[31] indicates contagion in Table 5.3 but not in Table 5.8.

[31] There are financial reports that Spain escaped the initial crisis.

Table 5.8: Dummy test for sub-period 1

African markets	R squared	Coefficients			Evidence of contagion[2]
		Unstandardised coefficient		*t*	
		β			
		Constant	*Dummy*	*Dummy*[1]	
Botswana	0.051	-0.028	0.040	**4.697*** **	**YES**
Côte d'Ivoire	0.165	0.028	0.075	**8.912*** **	**YES**
Egypt	0.066	0.155	0.088	**4.710*** **	**YES**
Mauritius	0.000	0.043	0.000	0.229	NO
Morocco	0.318	0.011	0.120	**13.846*** **	**YES**
Namibia	0.001	0.342	0.025	0.513	NO
Nigeria	0.012	0.043	0.000	**2.190** **	**YES**
South Africa	0.014	0.416	0.080	**2.426*** **	**YES**
Tunisia	0.013	0.066	0.001	**2.332*** **	**YES**
Zambia	0.000	-0.016	0.000	0.225	NO
Developed markets					
Canada	0.008	0.763	-0.046	-1.802	NO
France	0.035	0.713	-0.046	-3.906	NO
Germany	0.027	0.664	0.045	**3.387*** **	**YES**
Italy	0.013	0.531	-0.054	-2.372	NO
Japan	0.002	0.246	0.011	0.922	NO
Spain	0.002	0.602	0.014	0.981	NO
United Kingdom	0.000	0.665	0.000	-0.050	NO
Other markets					
China	0.170	0.059	0.117	**8.978*** **	**YES**
India	0.058	0.314	0.064	**5.004*** **	**YES**

[1]*Significant at 10%, **Significant at 5%, ***Significant at 1%. [2] Contagion is defined as statistical significance at 5% level

Namibia and Tunisia did not show robustness in respect to the cumulative impact of sub-period 1-2 (in the comparison-of-mean test results). However, Nigeria and the remaining African markets appear robust.

With the exception of Spain, results are robust in all developed markets. For Spain, contagion is found in Table 5.4 but not in Table 5.9. Other markets are also robust in the sub-period 1-2 timeframe.

Table 5.9: Cumulative dummy test on sub-period 1-2

African markets	R squared	Coefficients			Evidence of contagion[2]
		Unstandardised coefficient		*t*	
		β			
		Constant	*Dummy*	*Dummy*[1]	
Botswana	0.067	-0.028	0.042	**5.449*** **	**YES**
Côte d'Ivoire	0.239	0.028	0.085	**11.316*** **	**YES**
Egypt	0.106	0.155	0.101	**6.147*** **	**YES**
Mauritius	0.033	0.043	0.000	**3.746*** **	**YES**
Morocco	0.397	0.011	0.128	**16.553*** **	**YES**
Namibia	0.001	0.342	0.024	0.548	NO
Nigeria	0.012	0.043	0.000	**2.198** **	**YES**
South Africa	0.021	0.416	0.088	**2.971*** **	**YES**
Tunisia	0.015	0.066	0.001	**2.514*** **	**YES**
Zambia	0.000	-0.016	0.000	0.252	NO
Developed markets					
Canada	0.005	0.763	-0.033	-1.418	NO
France	0.034	0.713	-0.041	-3.851	NO
Germany	0.045	0.664	0.053	**4.470*** **	**YES**
Italy	0.012	0.531	-0.046	-2.281	NO
Japan	0.014	0.246	0.026	**2.427*** **	**YES**
Spain	0.003	0.602	0.015	1.136	NO
United Kingdom	0.001	0.665	0.003	0.486	NO
Other markets					
China	0.212	0.059	0.116	**10.340*** **	**YES**
India	0.128	0.314	0.089	**7.750*** **	**YES**

[1]*Significant at 10%, **Significant at 5%, ***Significant at 1%. [2]Contagion is defined as statistical significance at 5% level

Only Namibia shows an absence of robustness from the cumulative impact of sub-period 1-3 for the African markets. For the developed markets, UK is the only market where this is also the case. Contagion at 5% is found in the UK in Table 5.5 but not in Table 5.10.

Sub-period 1-4 provided the same result as in sub-period 1-3 for the African markets, whereas full robustness is found in the developed markets and other markets from the dummy test on the cumulative impact of sub-period 1-4.

This section can therefore be concluded by reporting;

- Full robustness across all markets in the long period;
- No robustness in Nigeria, Namibia, Tunisia and Spain in sub-period 1;

- No robustness in Namibia, Tunisia and Spain from the cumulative test on sub-period 1-2;
- No robustness in Namibia and UK in respect to the cumulative impact of sub-period 1-3;
- No robustness in Namibia in respect to the cumulative impact of sub-period 1-4.

All other markets show robustness.

Table 5.10: Cumulative dummy test on sub-period 1-3

		Coefficients			
		Unstandardised coefficient		t	
		β			
African markets	**R squared**	***Constant***	***Dummy***	***Dummy*** [1]	**Evidence of contagion** [2]
Botswana	0.107	-0.028	0.048	**7.067*****	**YES**
Côte d'Ivoire	0.309	0.028	0.092	**13.609*****	**YES**
Egypt	0.144	53.960	0.108	**7.346*****	**YES**
Mauritius	0.053	0.043	0.000	**4.861*****	**YES**
Morocco	0.466	0.011	0.132	**19.224*****	**YES**
Namibia	0.001	0.342	0.025	0.648	NO
Nigeria	0.007	0.043	0.000	**1.719****	**YES**
South Africa	0.032	0.416	0.099	**3.731*****	**YES**
Tunisia	0.006	0.066	0.001	1.576	NO
Zambia	0.000	-0.016	0.000	0.276	NO
Developed markets					
Canada	0.002	0.763	-0.018	-0.873	NO
France	0.030	0.713	-0.035	-3.679	NO
Germany	0.069	0.664	0.060	**5.653*****	**YES**
Italy	0.009	0.531	-0.036	-2.001	NO
Japan	0.045	0.246	0.043	**4.409*****	**YES**
Spain	0.006	0.602	0.020	**1.660****	**YES**
United Kingdom	0.004	0.665	0.007	1.249	NO
Other markets					
China	0.241	0.059	0.111	**11.329*****	**YES**
India	0.208	0.314	0.109	**10.460*****	**YES**

[1] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [2] Contagion is defined as statistical significance at 5% level

Table 5.11: Cumulative dummy test on sub-period 1-4

African markets	R squared	Coefficients			Evidence of contagion[2]
		Unstandardised coefficient		t	
		β			
		Constant	*Dummy*	*Dummy*[1]	
Botswana	0.284	-0.028	0.073	**13.139*** **	**YES**
Côte d'Ivoire	0.354	0.028	0.082	**15.377*** **	**YES**
Egypt	0.273	0.155	0.130	**11.229*** **	**YES**
Mauritius	0.069	0.043	0.000	**5.699*** **	**YES**
Morocco	0.593	0.011	0.141	**25.291*** **	**YES**
Namibia	0.002	0.342	0.027	0.856	NO
Nigeria	0.001	0.043	0.000	0.560	NO
South Africa	0.073	0.416	0.123	**5.896*** **	**YES**
Tunisia	0.004	0.066	0.000	1.243	NO
Zambia	0.000	-0.016	0.000	0.338	NO
Developed markets					
Canada	0.000	0.763	0.007	0.427	NO
France	0.024	0.713	-0.025	-3.345	NO
Germany	0.143	0.664	0.073	**8.628*** **	**YES**
Italy	0.002	0.531	-0.015	-1.004	NO
Japan	0.129	0.246	0.062	**7.955*** **	**YES**
Spain	0.019	0.602	0.027	**2.919*** **	**YES**
United Kingdom	0.025	0.665	0.016	**3.350*** **	**YES**
Other markets					
China	0.240	0.059	0.091	**11.547*** **	**YES**
India	0.373	0.314	0.138	**16.022*** **	**YES**

[1] *Significant at 10%, **Significant at 5%, ***Significant at 1%. [2] Contagion is defined as statistical significance at 5% level

5.6 CHAPTER CONCLUSION

The main purpose of this chapter is to check the evidence of contagion using a time-varying correlation. This chapter controls for the heteroscedasticity bias by using a GARCH process for the conditional variance system. The results illustrate that there is more contagion than the constant correlation coefficient analysis applied in Chapter 4 shows. This is evident in both the African and developed markets as well as the two comparative markets. The statistical method and correlation coefficient estimation are mainly different from the perception of Forbes and Rigobon (2002), which might be the reason that led to the difference in the empirical results.

The primary hypothesis that tests for evidence of contagion during the long crisis period found considerable evidences. The spikes in the VIX that made up the four short crisis sub-periods in this research also appear to be related to contagion effects. Evidence of contagion is found in:

1. African markets (Botswana, Côte d'Ivoire, Egypt, Mauritius and South Africa) and developed markets (Canada, France, Germany, Italy, Spain and the UK) in the long crisis period;
2. African markets (Botswana, Côte d'Ivoire, Egypt, Morocco, Namibia, South Africa) and developed markets (Germany and Spain) during sub-period 1 timeframe;
3. African markets (Botswana, Côte d'Ivoire, Egypt, Mauritius, Morocco, Namibia, Nigeria and South Africa) and developed markets (Germany, Japan and Spain) from the cumulative impact of sub-period 1-2;
4. African markets (Botswana, Côte d'Ivoire, Egypt, Mauritius, Morocco, Namibia, Nigeria and South Africa) and developed markets (Germany, Japan, Spain and the UK) in respect to sub-period 1-3;
5. African markets (Botswana, Côte d'Ivoire, Egypt, Mauritius, Morocco, Namibia and South Africa) and developed markets (Germany, Japan, Spain and the UK) in sub-period 1-4;
6. The two comparative markets China and India in all crisis periods including the long period;
7. Strong evidence of interdependence is found in the UK from the cumulative impact of sub-period 1-2 and, in Canada and France from the cumulative impact of sub-period 1-4.

An initial fall in correlation is found in Canada, France, Italy and the UK immediately after the onset of the crisis (sub-period 1). Correlations reduced from 76.3%, 71.3% and 53.1% to 71.7%, 66.6% and 47.7% in Canada, France and Italy, respectively, in sub-period 1. The reduction in correlation observed in the UK is very small. The value reduced from 66.54% to 66.49% after Lehman's announcement. This can be interpreted that stock markets in some developed markets responded relatively slowly to the initial falls in the US market. However, as the crisis period lengthens, some of the developed markets that appeared insulated during the first short sub-period became contaminated. Attempts to understand such behaviour can be best described from a *behavioural finance* perspective, to be discussed in Chapter 6.

It is generally believed that during crisis, variances and covariances of financial returns increase dramatically. Inspection of the pre-crisis and crisis variance and covariance charts shows that the crisis period is characterised by substantial increases in volatility. Associated with increases in both variances and covariances during the crisis periods are increases in correlations in most cases. This can be attributed to an increase in the volatility of either the economic and financial factors that jointly underlie financial returns (integration), or factors that cannot be measured (such as herding behaviour). This forms the bases of my model of interpretation and will be discussed in Chapter 6.

The next chapter of this thesis focuses on exploring the mechanism by which contagion occurs from a behavioural finance perspective. The focus will be the use of the preliminary model framework developed in Chapter 3 (Section 3.4, Figure 3.12) as a means of explaining the findings of Chapters 4 and 5. Behavioural finance theories of decision bias relating to features such as herding, anchoring, familiarity bias and information cascades will be discussed.

5.7 CHAPTER APPENDICES

Table A5.1a: VAR-based mean equations of US-African market pairs

Parameter	US	Botswana	Parameter	US	Côte d'Ivoire	Parameter	US	Egypt
Constant	-0.000247981	0.0000225875	Constant	-0.000267597	0.00103884	Constant	-0.000294488	-0.0000250047
US_1	0.848141***	-0.000911955	US_1	0.761054***	-0.114429	US_1	0.843851***	0.297883***
US_2	-0.906656***	-0.0102567	US_2	-0.798348***	0.316544	US_2	-0.827995***	-0.207069***
US_3	0.935474***	0.00377809	US_3	0.812013***	-0.232892	US_3	0.769903***	0.265367***
US_4	-0.898679***	0.00477794	US_4	-0.811138***	0.344552	US_4	-0.728195***	-0.196444**
US_5	0.777385***	0.0039999	US_5	0.760569***	-0.244667	US_5	0.715006***	0.302231***
US_6	-0.728634***	-0.00300836	US_6	-0.711443***	0.83366	US_6	-0.663666***	-0.240377***
US_7	0.740223***	-0.00510448	US_7	0.696819***	-0.650823	US_7	0.615036***	0.236593***
US_8	-0.748871***	0.0050247	US_8	-0.641278***	1.0268	US_8	-0.511027***	-0.112259
US_9	0.701012***	0.00113004	US_9	0.550134***	-1.15228	US_9	0.616576***	0.167681*
US_10	-0.472433***	-0.0249244	US_10	-0.381801***	0.958529	US_10	-0.757136***	-0.0681195
US_11	0.397712***	0.0250776	US_11	0.324758***	-1.22132	US_11	0.756519***	0.139035*
US_12	-0.358976***	-0.0215059	US_12	-0.257215***	0.55467	US_12	-0.738285***	-0.143365*
US_13	0.258597***	0.0156413	US_13	0.165687**	-0.855885	US_13	0.648702***	0.163821*
US_14	-0.18331**	-0.0153177	US_14	-0.141222**	0.132525	US_14	-0.611757***	-0.110264
US_15	0.206445***	0.0266707	US_15	0.150902***	-0.121769	US_15	0.525872***	0.143165
US_16	-0.18519***	-0.0164465	US_16	-0.141264***	0.0283379	US_16	-0.472964***	-0.190681**
US_17	0.0198845	0.0243765**	Côte d'Ivoire_1	0.00124261	0.00912045	US_17	0.337654***	0.101647

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1a: Continued

Parameter	US	Botswana	Parameter	US	Côte d'Ivoire	Parameter	US	Egypt
Botswana_1	0.20972	1.03281***	Côte d'Ivoire_2	0.00127434	-0.884578***	US_18	-0.285662***	-0.0644767
Botswana_2	-0.268635	-0.857985***	Côte d'Ivoire_3	-0.000412793	0.0226949	US_19	0.259176***	-0.0224867
Botswana_3	0.200823	0.871026***	Côte d'Ivoire_4	-0.000136584	-0.753358***	US_20	-0.107683**	0.110207**
Botswana_4	-0.162829	-0.778722***	Côte d'Ivoire_5	0.000907592	0.0421973	Egypt_1	0.014615	0.853817***
Botswana_5	0.188631	0.817571***	Côte d'Ivoire_6	0.000763215	-0.629418***	Egypt_2	0.0195467	-0.693679***
Botswana_6	-0.159374	-0.728922***	Côte d'Ivoire_7	0.0029472	0.0446737	Egypt_3	-0.118122*	0.583215***
Botswana_7	0.127376	0.729751***	Côte d'Ivoire_8	0.001967	-0.514396***	Egypt_4	0.0103543	-0.679963***
Botswana_8	0.13808	-0.593282***	Côte d'Ivoire_9	0.00222004	0.0417214	Egypt_5	0.0103543	-0.679963***
Botswana_9	-0.217799	0.570905***	Côte d'Ivoire_10	0.000876898	-0.408744***	Egypt_6	-0.111934	-0.560265***
Botswana_10	0.103613	-0.523839***	Côte d'Ivoire_11	0.00392616	0.0327717	Egypt_7	0.0737436	0.428475***
Botswana_11	-0.36725	0.489133***	Côte d'Ivoire_12	-0.000484143	-0.30523***	Egypt_8	0.0137626	-0.415015***
Botswana_12	0.228481	-0.405144***	Côte d'Ivoire_13	0.00468088	0.0211711	Egypt_9	0.104837	0.437439***
Botswana_13	-0.257718	0.364453***	Côte d'Ivoire_14	0.0025789	-0.197152***	Egypt_10	-0.109836	-0.439738***
Botswana_14	0.180406	-0.339406***	Côte d'Ivoire_15	0.00132724	0.0109721	Egypt_11	0.144707	0.418121***
Botswana_15	0.0349362	0.249835***	Côte d'Ivoire_16	-0.00241105	-0.0977763**	Egypt_12	-0.0941357	-0.373146***
Botswana_16	-0.0469268	-0.126257**				Egypt_13	0.147015*	0.321175***
Botswana_17	0.0390386	0.105834***				Egypt_14	-0.0845706	-0.285059***
						Egypt_15	0.114242	0.28451***
						Egypt_16	-0.0693059	-0.177189**
						Egypt_17	-0.0116121	0.149648**
						Egypt_18	-0.0419551	-0.148157**
						Egypt_19	0.0472126	0.123812**
						Egypt_20	-0.0339205	-0.111248**

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1b: VAR-based mean equations of US-African market pairs (continued)

Parameter	US	Mauritius	Parameter	US	Morocco	Parameter	US	Namibia
Constant	-0.000336995	0.000335372	Constant	-0.000222834	0.0000765058	Constant	-0.000507353	0.000120359
US_1	0.793082***	0.160765***	US_1	0.801334***	0.0566649***	US_1	0.827268***	0.314683***
US_2	-0.811698***	-0.128103***	US_2	-0.82402***	-0.0534966**	US_2	-0.932044***	-0.0693791*
US_3	0.81459***	0.186136***	US_3	0.823764***	0.0447786	US_3	0.961072***	0.251248***
US_4	-0.765578***	-0.112582***	US_4	-0.795755***	-0.0540609	US_4	-0.970677***	-0.194469***
US_5	0.613725***	0.135185***	US_5	0.708166***	-0.0342074	US_5	0.866808***	0.261528***
US_6	-0.527911***	-0.0469241	US_6	-0.652535***	0.0253673	US_6	-0.817644***	-0.198052***
US_7	0.467789***	0.0109326	US_7	0.581901***	-0.0216948	US_7	0.721089***	0.244634***
US_8	-0.395332***	0.0586797	US_8	-0.483823***	0.0444187	US_8	-0.597428***	-0.163445**
US_9	0.330434***	-0.0071419	US_9	0.341167***	-0.00601887	US_9	0.5222***	0.231997***
US_10	-0.237206***	0.0208079	US_10	-0.270492***	0.0312336	US_10	-0.442199***	-0.12971**
US_11	0.221815***	0.0394843	US_11	0.280707***	-0.00603177	US_11	0.331528***	0.126137**
US_12	-0.189021***	0.0239741	US_12	-0.196925***	-0.0101705	US_12	-0.185343***	-0.0827061
US_13	0.0826628	-0.0367668	US_13	0.123277***	0.0194279	US_13	0.136196***	0.105102**
US_14	-0.0814977**	0.00120518	Morocco_1	0.0086715	1.2481***	US_14	-0.138554***	-0.0308701

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1b: Continued

Parameter	US	Mauritius	Parameter	US	Morocco	Parameter	US	Namibia
Mauritius_1	-0.0494249	1.12215***	Morocco_2	-0.207467*	-1.2398***	Namibia_1	-0.0102732	0.491311***
Mauritius_2	-0.0389908	-1.10707***	Morocco_3	0.135234	1.11434***	Namibia_2	0.0587336	-0.719279***
Mauritius_3	0.0698953	1.03961***	Morocco_4	-0.067774	-0.968949***	Namibia_3	-0.0658213	0.436048***
Mauritius_4	0.130196	-0.945278***	Morocco_5	0.110584	0.866743***	Namibia_4	0.125745*	-0.540391***
Mauritius_5	-0.0858987	0.788075***	Morocco_6	-0.114826	-0.820202***	Namibia_5	-0.0816216	0.385139***
Mauritius_6	-0.0444995	-0.635612***	Morocco_7	0.0714969	0.700267***	Namibia_6	0.115611	-0.460951***
Mauritius_7	0.188438	0.573427***	Morocco_8	-0.145116	-0.616111***	Namibia_7	-0.115696	0.331112***
Mauritius_8	-0.348661**	-0.514064***	Morocco_9	0.120761	0.480514***	Namibia_8	0.157687**	-0.364285***
Mauritius_9	0.313608**	0.423662***	Morocco_10	-0.120542	-0.359611***	Namibia_9	-0.142098*	0.202549***
Mauritius_10	-0.271121*	-0.303561***	Morocco_11	0.208572	0.256254***	Namibia_10	0.136824*	-0.22584***
Mauritius_11	0.341392***	0.25415***	Morocco_12	-0.186589	-0.181428***	Namibia_11	-0.150038**	0.109785**
Mauritius_12	-0.208294*	-0.187529**	Morocco_13	0.151759*	0.0678412*	Namibia_12	0.136153**	-0.143383***
Mauritius_13	0.109002	0.136598**				Namibia_13	-0.0370755	0.0690935
Mauritius_14	0.0382463	-0.072475*				Namibia_14	0.0874145*	-0.0513732

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1c: VAR-based mean equations of US-African market pairs (continued)

Parameter	US	Nigeria	Parameter	US	South Africa	Parameter	US	Tunisia	Parameter	US	Zambia
Constant	-0.000273479	-0.000111508	Constant	-0.000247763	0.000228094	Constant	-0.000265673	0.000348529**	Constant	-0.000230671	0.000129546
US_1	0.868783***	-0.00573771	US_1	0.820951***	0.414607***	US_1	0.832808***	0.0462129***	US_1	0.806533***	0.00430791
US_2	-0.955158***	0.014587	US_2	-0.900704***	-0.314894***	US_2	-0.890044***	-0.0569201***	US_2	-0.838544***	0.0102298
US_3	0.989056***	-0.0225446	US_3	0.917167***	0.376997***	US_3	0.904874***	0.0798249***	US_3	0.814658***	-0.0379404
US_4	-0.942205***	0.0345189	US_4	-0.922254***	-0.308***	US_4	-0.875279***	-0.0714654***	US_4	-0.838672***	0.00909525
US_5	0.841968***	-0.0294286	US_5	0.815594***	0.388466***	US_5	0.772647***	0.0930839***	US_5	0.756979***	0.00553529
US_6	-0.815471***	0.0797036*	US_6	-0.770753***	-0.338073***	US_6	-0.666283***	-0.0602069**	US_6	-0.65027***	-0.0194253
US_7	0.7865***	-0.0248666	US_7	0.706319***	0.364245***	US_7	0.628686***	0.066961**	US_7	0.593104***	0.0197087
US_8	-0.708016***	0.0981366*	US_8	-0.580579***	-0.324841***	US_8	-0.555322***	-0.0614581**	US_8	-0.487055***	0.0125946
US_9	0.640623***	-0.0700756	US_9	0.544617***	0.333221***	US_9	0.445642***	0.0155004	US_9	0.497933***	0.0308036
US_10	-0.439688***	0.0686891	US_10	-0.480801***	-0.307887***	US_10	-0.338009***	0.0173539	US_10	-0.509175***	0.0410773
US_11	0.327271***	-0.0564575	US_11	0.410843***	0.300383***	US_11	0.33087***	0.00450211	US_11	0.383432***	-0.00841824
US_12	-0.147964*	0.0816598*	US_12	-0.246259***	-0.142778**	US_12	-0.272785***	0.0195184	US_12	-0.253213***	0.0467861
US_13	0.108923	-0.0538371	US_13	0.188491***	0.106111*	US_13	0.196052**	-0.00921278	US_13	0.247184***	-0.0396192
US_14	-0.0970658	0.0543996	US_14	-0.253409***	-0.150572***	US_14	-0.148699*	-0.000121465	US_14	-0.205204***	0.0440577
US_15	0.0227911	-0.0194923	US_15	0.130612***	0.0699395	US_15	0.146924*	0.0134535	US_15	0.10456***	-0.0223351
US_16	-0.10382**	0.0281899	South Africa_1	0.0234243	0.774558***	US_16	-0.14846**	0.00387222	Zambia_1	-0.0206265	0.742146***

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1c: Continued

Parameter	US	Nigeria	Parameter	US	South Africa	Parameter	US	Tunisia	Parameter	US	Zambia
Nigeria_1	-0.0183255	1.63305***	South Africa_2	0.000428992	-0.765244***	US_17	0.0519112	0.0137635	Zambia_2	-0.0299841	-0.679274***
Nigeria_2	-0.101161	-1.51421***	South Africa_3	-0.00319	0.578608***	US_18	-0.0412556	-0.0336315**	Zambia_3	-0.0736832	0.637717***
Nigeria_3	0.0893297	1.25744***	South Africa_4	0.0577121	-0.648874***	US_19	0.0727986*	0.030339**	Zambia_4	0.0590814	-0.569851***
Nigeria_4	0.0576313	-1.21468***	South Africa_5	-0.108148	0.47963***	Tunisia_1	0.23468*	1.10024***	Zambia_5	0.00780087	0.647647***
Nigeria_5	-0.266158	1.23272***	South Africa_6	0.227092**	-0.418026***	Tunisia_2	-0.213732	-0.984914***	Zambia_6	-0.00245961	-0.472082***
Nigeria_6	0.25691	-1.17173***	South Africa_7	-0.288825***	0.344736***	Tunisia_3	0.159957	0.922717***	Zambia_7	-0.0220571	0.544742***
Nigeria_7	-0.021964	0.99261***	South Africa_8	0.261744***	-0.318328***	Tunisia_4	0.153129	-0.923656***	Zambia_8	0.179635	-0.442323***
Nigeria_8	-0.00323142	-0.847925***	South Africa_9	-0.23823**	0.242352***	Tunisia_5	-0.425503	0.865238***	Zambia_9	-0.188277*	0.443386***
Nigeria_9	0.0276819	0.716375***	South Africa_10	0.244042***	-0.198074**	Tunisia_6	-0.000203391	-0.871164***	Zambia_10	0.179277	-0.29849***
Nigeria_10	-0.107406	-0.604591***	South Africa_11	-0.283841***	0.0441514	Tunisia_7	0.071113	0.783551***	Zambia_11	-0.189944*	0.289139***
Nigeria_11	0.21685	0.572715***	South Africa_12	0.25041***	-0.0249422	Tunisia_8	-0.26309	-0.657747***	Zambia_12	0.165977*	-0.195265***
Nigeria_12	-0.200983	-0.491803***	South Africa_13	-0.209826***	0.00571371	Tunisia_9	0.440326	0.720553***	Zambia_13	-0.151574*	0.165433***
Nigeria_13	0.147527	0.441201***	South Africa_14	0.258137***	0.0997327*	Tunisia_10	-0.318168	-0.69737***	Zambia_14	0.131675	-0.0463812
Nigeria_14	-0.11134	-0.390253***	South Africa_15	-0.126603***	-0.0322299	Tunisia_11	0.0702937	0.693834***	Zambia_15	-0.0508292	0.00631918
Nigeria_15	0.128754	0.251533***				Tunisia_12	0.180435	-0.63024***			
Nigeria_16	-0.103783	-0.094948**				Tunisia_13	-0.0899513	0.594993***			
						Tunisia_14	-0.114423	-0.532215***			
						Tunisia_15	0.370268	0.405029***			
						Tunisia_16	-0.222677	-0.329488***			
						Tunisia_17	-0.0302346	0.302493***			
						Tunisia_18	0.113803	-0.260468***			
						Tunisia_19	-0.0778145	0.088047**			

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1d: VAR-based mean equations of US-developed market pairs

Parameter	US	Canada	Parameter	US	France	Parameter	US	Germany
Constant	-0.000195771	0.0000355367	Constant	-0.000256432	-0.000320425	Constant	-0.000277106	0.0000610939
US_1	1.00414***	0.226922***	US_1	0.904377***	0.629592***	US_1	0.786129***	0.436425***
US_2	-0.962072***	-0.0634683	US_2	-0.887017***	-0.310371***	US_2	-0.930259***	-0.306612***
US_3	0.926242***	0.200274**	US_3	1.06187***	0.613502***	US_3	0.933405***	0.461279***
US_4	-0.854219***	-0.113407	US_4	-1.03913***	-0.472128***	US_4	-1.04089***	-0.510349***
US_5	0.778151***	0.09243	US_5	0.998738***	0.593467***	US_5	0.88548***	0.484283***
US_6	-0.863449***	-0.131286	US_6	-0.881777***	-0.491825***	US_6	-0.874118***	-0.442188***
US_7	0.783429***	0.0373304	US_7	0.789728***	0.407107***	US_7	0.837228***	0.460668***
US_8	-0.691579***	-0.0027005	US_8	-0.625448***	-0.343831***	US_8	-0.60101***	-0.236842**
US_9	0.695532***	0.133484	US_9	0.599372***	0.317042***	US_9	0.641321***	0.3066***
US_10	-0.481513***	-0.0189567	US_10	-0.401035***	-0.0695224	US_10	-0.508739***	-0.0544521
US_11	0.497388***	0.086383	US_11	0.378523***	0.100501	US_11	0.433159***	0.164889
US_12	-0.43985***	-0.0523765	US_12	-0.0939691	0.155712	US_12	-0.262959**	0.0779099
US_13	0.44564***	0.151787	US_13	0.0853071	-0.103099	US_13	0.187805	-0.0383002
US_14	-0.496073***	-0.209882**	US_14	-0.104749	0.117024	US_14	-0.216753*	0.0596571
US_15	0.34835***	0.191689**	US_15	-0.0280194	-0.159758**	US_15	0.118741	-0.107536
US_16	-0.130755*	-0.0544921	US_16	0.0941707	0.198175***	US_16	-0.0259287	0.172371*

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1d: Continued

Parameter	US	Canada	Parameter	US	France	Parameter	US	Germany
Canada_1	-0.280473***	0.664384***	US_17	-0.204948***	-0.195817***	US_17	0.0685791	-0.083511
Canada_2	0.264202***	-0.811329***	France_1	-0.092844	0.426305***	US_18	-0.160082*	-0.0154566
Canada_3	-0.177271	0.758813***	France_2	-0.0310254	-0.713457***	US_19	0.134531*	0.0913538
Canada_4	0.123378	-0.775095***	France_3	-0.136796*	0.380039***	US_20	-0.140549**	-0.0699313
Canada_5	-0.112342	0.658208***	France_4	0.180354**	-0.381336***	Germany_1	0.0826006	0.639939***
Canada_6	0.227337	-0.614014***	France_5	-0.23688**	0.217826***	Germany_2	-0.0283822	-0.751446***
Canada_7	-0.200494	0.650085***	France_6	0.212777**	-0.206566**	Germany_3	0.0213759	0.552011***
Canada_8	0.190834	-0.592385***	France_7	-0.182619*	0.232566***	Germany_4	0.129782	-0.405505***
Canada_9	-0.240412	0.406687**	France_8	0.104531	-0.216718**	Germany_5	-0.0474096	0.367681***
Canada_10	0.151743	-0.387598**	France_9	-0.150727	0.132698	Germany_6	0.085271	-0.325902***
Canada_11	-0.237747	0.214295	France_10	0.0601822	-0.295603***	Germany_7	-0.139518	0.214633**
Canada_12	0.208333	-0.171551	France_11	-0.170316*	0.115233	Germany_8	-0.008676	-0.360042***
Canada_13	-0.219971	0.0883683	France_12	0.00719748	-0.237158***	Germany_9	-0.0615429	0.228572**
Canada_14	0.261073**	0.00600416	France_13	0.0098315	0.150639*	Germany_10	0.0464379	-0.341157***
Canada_15	-0.186754*	-0.0490015	France_14	0.0318665	-0.0992538	Germany_11	-0.08002	0.194075**
Canada_16	0.0354112	-0.0258985	France_15	0.0345486	0.105752	Germany_12	0.0114898	-0.305009***
			France_16	0.0042495	-0.0372738	Germany_13	0.0926674	0.236201**
			France_17	0.129214**	0.112855**	Germany_14	-0.106581	-0.264697***
						Germany_15	0.130348	0.232748***
						Germany_16	-0.157729*	-0.25078***
						Germany_17	0.069041	0.19291**
						Germany_18	0.00610674	-0.19253**
						Germany_19	0.0301795	0.125271*
						Germany_20	0.0415113	-0.0589505

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1e: VAR-based mean equations of US-developed market pairs (continued)

Parameter	US	Italy	Parameter	US	Japan	Parameter	US	Spain	Parameter	US	UK
Constant	-0.000262278	-0.00035872	Constant	-0.000276026	-0.000520024	Constant	-0.000200571	-0.0000610761	Constant	-0.000202129	0.0000221085
US_1	0.900798***	0.598985***	US_1	0.784581***	0.592296***	US_1	0.872202***	0.465405***	US_1	0.844048***	0.503093***
US_2	-0.854961***	-0.313975***	US_2	-0.777398***	-0.396919***	US_2	-0.887305***	-0.329917***	US_2	-0.869365***	-0.265746***
US_3	0.969339***	0.451877***	US_3	0.811821***	0.565569***	US_3	0.999776***	0.466521***	US_3	0.974925***	0.489304***
US_4	-0.964102***	-0.329203***	US_4	-0.730536***	-0.444069***	US_4	-0.94137***	-0.395758***	US_4	-0.977741***	-0.385433***
US_5	0.939348***	0.407231***	US_5	0.719937***	0.47998***	US_5	1.02071***	0.537608***	US_5	0.935698***	0.499625***
US_6	-0.77195***	-0.298354***	US_6	-0.576135***	-0.37376***	US_6	-0.777184***	-0.421387***	US_6	-0.79638***	-0.342514***
US_7	0.799299***	0.29378***	US_7	0.620603***	0.440001***	US_7	0.77326***	0.361743***	US_7	0.739077***	0.367749***
US_8	-0.583637***	-0.251941***	US_8	-0.483349***	-0.330056***	US_8	-0.59188***	-0.293654***	US_8	-0.615012***	-0.319837***
US_9	0.654546***	0.310363***	US_9	0.473337***	0.379254***	US_9	0.52149***	0.282857***	US_9	0.595504***	0.292533***
US_10	-0.486606***	-0.14652**	US_10	-0.4162***	-0.212051***	US_10	-0.404847***	-0.16063*	US_10	-0.435645***	-0.145876
US_11	0.484481***	0.201103***	US_11	0.410199***	0.230324***	US_11	0.26648**	0.0915207	US_11	0.482362***	0.172698*
US_12	-0.295791***	-0.0218614	US_12	-0.343098***	-0.228769***	US_12	-0.067716	0.0905559	US_12	-0.20794*	0.0142124
US_13	0.222793**	0.0535993	US_13	0.24082***	0.195635**	US_13	0.0140936	-0.0461816	US_13	0.243477**	0.106557
US_14	-0.328432***	-0.0715174	US_14	-0.232381***	-0.167328**	US_14	-0.00837936	0.130325*	US_14	-0.238911**	-0.0235326
US_15	0.19418**	-0.045128	US_15	0.203972**	0.175821**	US_15	-0.032001	-0.101793	US_15	0.200834**	0.0482281
US_16	-0.192928**	-0.0118995	US_16	-0.256573***	-0.137555**	US_16	0.113157*	0.193821***	US_16	-0.0593052	0.0803737
US_17	0.0970382	-0.00935662	US_17	0.0340156	0.0436672	US_17	-0.21577***	-0.147255***	US_17	-0.0594943	-0.113298**
US_18	-0.198827***	-0.0377585	US_18	-0.118024**	-0.0241479	Spain_1	-0.0852669	0.640516***	US_18	-0.137423**	-0.0703351
US_19	0.126442*	0.033788	US_19	0.122449**	0.0490808	Spain_2	-0.0193417	-0.725631***	UK_1	-0.0566351	0.488109***
US_20	-0.0247446	-0.013433	Japan_1	-0.00728858	0.692504***	Spain_3	-0.104305	0.558259***	UK_2	-0.00987198	-0.708869***

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1e: Continued

Parameter	US	Italy	Parameter	US	Japan	Parameter	US	Spain	Parameter	US	UK
Italy_1	-0.153334**	0.616477***	Japan_2	-0.0292745	-0.78964***	Spain_4	0.0486452	-0.52446***	UK_3	-0.106692	0.386382***
Italy_2	-0.0168999	-0.691368***	Japan_3	-0.0639319	0.57803***	Spain_5	-0.260964***	0.316537***	UK_4	0.175631*	-0.371437***
Italy_3	-0.0201834	0.542332***	Japan_4	-0.00672457	-0.600706***	Spain_6	0.11887	-0.352959***	UK_5	-0.271419***	0.186892**
Italy_4	0.069732	-0.507647***	Japan_5	-0.134119	0.493116***	Spain_7	-0.156941	0.299663***	UK_6	0.211945**	-0.293937***
Italy_5	-0.214714*	0.458338***	Japan_6	0.0653828	-0.55448***	Spain_8	0.122715	-0.319696***	UK_7	-0.169526	0.283149***
Italy_6	0.161111	-0.468407***	Japan_7	-0.0379752	0.474034***	Spain_9	-0.094281	0.284517***	UK_8	0.143358	-0.251707***
Italy_7	-0.232918*	0.481669***	Japan_8	-0.0729821	-0.520701***	Spain_10	0.105786	-0.290467***	UK_9	-0.167732	0.233042***
Italy_8	0.0978354	-0.475916***	Japan_9	0.146115	0.380468***	Spain_11	-0.0745795	0.246171***	UK_10	0.0628509	-0.292945***
Italy_9	-0.179358	0.334532***	Japan_10	-0.0887781	-0.427003***	Spain_12	-0.0417629	-0.260952***	UK_11	-0.254252**	0.14296*
Italy_10	0.165715	-0.354923***	Japan_11	-0.00568646	0.435107***	Spain_13	0.12211	0.231525***	UK_12	0.049615	-0.24485***
Italy_11	-0.261358*	0.212961**	Japan_12	0.0272969	-0.343675***	Spain_14	-0.122393	-0.258313***	UK_13	-0.0523745	0.0872175
Italy_12	0.233428*	-0.18742**	Japan_13	0.011152	0.313397***	Spain_15	0.0943798	0.179508**	UK_14	0.0348015	-0.111527
Italy_13	0.0141931	0.248476***	Japan_14	0.0591678	-0.234492***	Spain_16	-0.0133688	-0.123341**	UK_15	-0.0736691	0.0286635
Italy_14	0.0116419	-0.124082	Japan_15	-0.0187322	0.204972***	Spain_17	0.166484***	0.151438***	UK_16	0.070546	-0.0498886
Italy_15	0.112648	0.238756***	Japan_16	0.114078	-0.160092**				UK_17	0.072636	0.118885**
Italy_16	0.0134826	-0.11046	Japan_17	0.0998907	0.119406**				UK_18	0.115283*	0.00264039
Italy_17	-0.0644874	0.0729602	Japan_18	0.0198499	-0.106474**						
Italy_18	0.219488**	-0.0561886	Japan_19	-0.126224***	0.0162089						
Italy_19	-0.25373***	-0.0295603									
Italy_20	0.121108**	-0.0577682*									

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1f: VAR-based mean equations of US-other market pairs

Parameter	US	China	Parameter	US	India
Constant	-0.0002845	0.000214255	Constant	-0.000331978	0.000484172
US_1	0.855067***	0.234565***	US_1	0.788999***	0.400645***
US_2	-0.947673***	-0.194429***	US_2	-0.801605***	-0.127473**
US_3	0.974339***	0.137539*	US_3	0.82306***	0.323879***
US_4	-0.976634***	-0.0882915	US_4	-0.717489***	-0.177862**
US_5	0.902781***	0.123536	US_5	0.66775***	0.182972**
US_6	-0.822611***	0.028695	US_6	-0.637725***	-0.0413718
US_7	0.790014***	-0.0185929	US_7	0.66351***	0.16629*
US_8	-0.718996***	0.113568	US_8	-0.632983***	-0.0736567
US_9	0.658358***	-0.0702651	US_9	0.557766***	0.0194671
US_10	-0.552596***	0.0471972	US_10	-0.463129***	0.0975065
US_11	0.565593***	-0.0786015	US_11	0.436824***	0.00091758
US_12	-0.45266***	0.10337	US_12	-0.44908***	0.0329237
US_13	0.409778***	-0.0988853	US_13	0.353821***	0.0340768
US_14	-0.415922***	0.0303365	US_14	-0.331367***	-0.0248387
US_15	0.372502***	0.0197155	US_15	0.346681***	0.0318759
US_16	-0.30352***	0.0251568	US_16	-0.456104***	-0.123647
US_17	0.212871***	0.00220752	US_17	0.30743***	0.142238*
US_18	-0.22801***	-0.076174	US_18	-0.277668***	-0.198573***
US_19	0.2194***	0.0445372	US_19	0.247714***	0.138598**
US_20	-0.132354***	-0.040195	US_20	-0.134884***	-0.143056***

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.1f: Continued

Parameter	US	China	Parameter	US	India
China_1	0.0116064	0.885313***	India_1	-0.00875436	0.814384***
China_2	-0.0338925	-0.808613***	India_2	-0.0242854	-0.901714***
China_3	0.0186294	0.812302***	India_3	-0.018499	0.759776***
China_4	-0.0749971	-0.711835***	India_4	-0.0447736	-0.796144***
China_5	-0.0102389	0.607508***	India_5	0.0656823	0.670258***
China_6	-0.0191037	-0.574031***	India_6	-0.0805467	-0.73329***
China_7	-0.015415	0.545016***	India_7	0.0598169	0.679363***
China_8	-0.00606105	-0.560961***	India_8	-0.0413573	-0.52658***
China_9	0.0275321	0.516315***	India_9	0.0636303	0.458464***
China_10	-0.00422666	-0.427957***	India_10	-0.0894861	-0.431151***
China_11	0.0694359	0.4179***	India_11	0.158014*	0.375968***
China_12	-0.037427	-0.343613***	India_12	-0.123062	-0.327857***
China_13	0.0148077	0.393854***	India_13	0.127526	0.321321***
China_14	-0.0205044	-0.320494***	India_14	-0.073253	-0.195856**
China_15	0.101011	0.266597***	India_15	0.143348*	0.195339**
China_16	-0.06024	-0.258514***	India_16	-0.0707471	-0.1148
China_17	0.0682894	0.207617***	India_17	0.155524**	0.125246
China_18	-0.0317032	-0.122728*	India_18	-0.13477**	-0.128944*
China_19	0.00713942	0.06624	India_19	0.0433392	0.0790449
China_20	0.037641	-0.0455147	India_20	-0.0419083	-0.026195

***Significant at 1%; Significant at 5%;* Significant at 10%

Table A5.2a: Variance equations (GARCH 1, 1) for US and African markets

US					African markets				
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Botswana**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6306	1.4290	0.1535		Constant	2.2478	2.3660	0.0183	
Alpha	0.0841	4.4690	0.0000		Alpha	0.1544	1.8740	0.0614	
Beta	0.9108	48.1200	0.0000	2200.9730	Beta	0.5038	3.7580	0.0002	2956.7230
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Côte d'Ivoire**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.8179	1.8020	0.0720		Constant	0.1608	0.9621	0.3364	
Alpha	0.0973	4.0430	0.0001		Alpha	9.0580	1.0050	0.3152	
Beta	0.8951	38.3200	0.0000	2216.0790	Beta	0.0792	0.6159	0.5382	1229.7560
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Egypt**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	1.4463	1.5810	0.1145		Constant	0.0286	1.4440	0.1495	
Alpha	0.1066	4.1370	0.0000		Alpha	0.1893	2.5560	0.0109	
Beta	0.8793	33.2400	0.0000	1668.6840	Beta	0.8129	15.2600	0.0000	1649.5190
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Mauritius**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	1.2186	1.8910	0.0591		Constant	6.4849	2.0110	0.0448	
Alpha	0.0940	3.9160	0.0001		Alpha	0.5486	2.9080	0.0038	
Beta	0.8919	34.9000	0.0000	2239.6190	Beta	0.3942	2.3580	0.0187	2519.3130
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Morocco**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	1.2005	1.7450	0.0815		Constant	2.2877	1.8670	0.0624	
Alpha	0.0886	3.4310	0.0006		Alpha	0.1843	3.1480	0.0017	
Beta	0.8980	31.7700	0.0000	2215.0860	Beta	0.7270	7.6780	0.0000	2604.5450
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Namibia**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.0312	1.8220	0.0690		Constant	0.3527	1.3550	0.1760	
Alpha	0.0842	3.9240	0.0001		Alpha	0.0347	1.1410	0.2543	
Beta	0.9066	40.8900	0.0000	1819.2160	Beta	0.8104	22.1800	0.0000	1872.5470

Table A5.2a: Continued

US					African markets				
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Nigeria**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.9358	1.7320	0.0837		Constant	0.7165	1.8380	0.0666	
Alpha	0.0771	3.9410	0.0001		Alpha	0.0846	2.6000	0.0095	
Beta	0.9110	41.7400	0.0000	2205.7120	Beta	0.8840	21.5100	0.0000	2569.2440
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**South Africa**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6161	1.6250	0.1047		Constant	0.8757	1.7270	0.0847	
Alpha	0.0821	3.9690	0.0001		Alpha	0.0858	4.6520	0.0000	
Beta	0.9114	44.5200	0.0000	2274.7260	Beta	0.9029	46.9000	0.0000	2293.7550
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Tunisia**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6848	1.6300	0.1035		Constant	1.3111	1.1930	0.2335	
Alpha	0.0957	5.3520	0.0000		Alpha	0.2084	2.1460	0.0323	
Beta	0.8971	51.5000	0.0000	2212.2770	Beta	0.6471	3.1450	0.0017	2897.2830
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Zambia**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.7813	0.9071	0.0782		Constant	4.1858	1.4280	0.1538	
Alpha	0.0833	4.4750	0.0000		Alpha	0.0682	1.9470	0.0520	
Beta	0.9071	48.3100	0.0000	2238.6260	Beta	0.8235	12.0500	0.0000	2414.0480

Table A5.2b: DCC equations for correlation estimates between US and African markets

Botswana	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	-0.0242	-0.4290	0.6681	
Alpha	0.0093	1.2040	0.2292	
Beta	0.9787	45.7200	0.0000	5283.4600
Cote d'Ivoire	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.0229	0.4620	0.6442	
Alpha	0.0193	1.4590	0.1450	
Beta	0.9519	20.1600	0.0000	3712.0520
Egypt	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.1669	2.3970	0.0169	
Alpha	0.0192	1.5420	0.1236	
Beta	0.9473	48.7400	0.0000	3355.1590
Mauritius	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.0433	1.1110	0.2669	
Alpha	0.0000	0.0145	0.9885	
Beta	0.7698	1.8690	0.0621	4804.4620
Morocco	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.0121	0.2334	0.8155	
Alpha	0.0144	1.5530	0.1210	
Beta	0.9472	50.2800	0.0000	4856.2860
Namibia	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.7665	4.7670	0.0000	
Alpha	0.0181	0.9819	0.0291	
Beta	0.9819	118.2000	0.0000	3879.3450
Nigeria	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.0427	1.0430	0.2972	
Alpha	0.0000	0.0002	0.9998	
Beta	0.0030	0.0037	0.9971	4785.2420
South Africa	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.6850	3.8750	0.0001	
Alpha	0.0185	1.6040	0.1091	
Beta	0.9810	91.8500	0.0000	4654.1010
Tunisia	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.0659	1.7490	0.0807	
Alpha	0.0018	0.0249	0.9801	
Beta	0.2860	0.0040	0.9968	5118.8220
Zambia	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	-0.0163	-0.4619	0.6443	
Alpha	0.0000	0.0000	0.9999	
Beta	0.8418	5.5090	0.0000	4716.6350

Rho is the correlation targeting parameter.

Table A5.2c: Variance equations (GARCH 1, 1) for US and developed markets

US					Developed markets				
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Canada**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6181	1.7560	0.0795		Constant	0.4668	1.5990	0.1102	
Alpha	0.0792	4.8390	0.0000		Alpha	0.0825	4.8320	0.0000	
Beta	0.9140	59.2300	0.0000	2307.8230	Beta	0.9126	54.9800	0.0000	2345.5570
US	**Parameter**	**T-value**		**Log likelihood**	**France**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.7351	1.5430	0.1234		Constant	0.7245	1.4470	0.1483	
Alpha	0.0791	4.0290	0.0001		Alpha	0.0720	3.2110	0.0014	
Beta	0.9126	43.6400	0.0000	2305.6760	Beta	0.9185	36.6400	0.0000	2345.1040
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Germany**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.7165	1.6390	0.1016		Constant	0.9929	1.5740	0.1160	
Alpha	0.0819	4.5110	0.0000		Alpha	0.0761	3.7270	0.0002	
Beta	0.9099	4.5110	0.0000	2287.5780	Beta	0.9122	43.4800	0.0000	2300.4770
US	**Parameter**	**T-value**		**Log likelihood**	**Italy**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6491	1.5340	0.1256		Constant	0.4681	1.2360	0.2167	
Alpha	0.0814	4.5630	0.0000		Alpha	0.1064	2.2730	0.0234	
Beta	0.0814	50.0700	0.0000	2277.4360	Beta	0.8860	19.0100	0.0000	2552.1730
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Japan**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.5068	1.5240	0.1279		Constant	1.4812	1.5400	0.1240	
Alpha	0.0925	5.8760	0.0000		Alpha	0.1323	2.4020	0.0166	
Beta	0.9041	63.8500	0.0000	2182.7010	Beta	0.8470	15.4400	0.0000	2275.5900
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**Spain**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6973	1.5510	0.1213		Constant	1.0526	1.3710	0.1710	
Alpha	0.0734	4.0800	0.0001		Alpha	0.0702	2.6790	0.0076	
Beta	0.9188	48.2400	0.0000	2284.8630	Beta	0.9150	28.0800	0.0000	2325.8070
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**UK**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.6715	1.5190	0.1292		Constant	0.4358	1.2920	0.1967	
Alpha	0.0850	4.5180	0.0000		Alpha	0.0770	4.5260	0.0000	
Beta	0.9087	47.7200	0.0000	2274.8890	Beta	0.9177	55.2400	0.0000	2366.0840

Rho is the correlation targeting parameter

Table A5.2d: DCC equations for correlations estimates between US and developed markets

Canada	Parameter	T-value	T-probability	Log likelihood
Rho	0.9407	45.0500	0.0000	
Alpha	0.0330	4.6770	0.0000	
Beta	0.9670	131.8000	0.0000	5000.9420
France	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.8343	13.0900	0.0000	
Alpha	0.0150	3.1370	0.0018	
Beta	0.9838	218.8000	0.0000	4914.3670
Germany	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.7840	8.0600	0.0000	
Alpha	0.0148	0.9824	0.1441	
Beta	0.9824	91.2800	0.0000	4845.0780
Italy	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.7364	3.6700	0.0003	
Alpha	0.0164	0.9751	0.3299	
Beta	0.9836	61.7200	0.0000	4957.2370
Japan	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.2450	4.3390	0.0000	
Alpha	0.0146	1.3220	0.1866	
Beta	0.9528	35.4700	0.0000	4486.1520
Spain	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.7352	6.0540	0.0000	
Alpha	0.0139	2.1980	0.0283	
Beta	0.9853	167.7000	0.0000	4805.4930
UK	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.7493	8.5060	0.0000	
Alpha	0.0105	2.5010	0.0126	
Beta	0.9894	216.3000	0.0000	4862.5810

Table A5.2e: Variance equations (GARCH 1, 1) for US and other markets

US					Other markets				
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**China**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.8393	1.5440	0.1231		Constant	0.0521	0.9866	0.3242	
Alpha	0.0994	3.3680	0.0008		Alpha	0.0338	1.5410	0.1238	
Beta	0.8950	35.1300	0.0000	2157.0030	Beta	0.9312	19.9600	0.0000	1904.2710
US	**Parameter**	**T-value**	**T-probability**	**Log likelihood**	**India**	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Constant	0.7828	1.5000	0.1340		Constant	0.0186	1.1700	0.2425	
Alpha	0.0987	4.7110	0.0000		Alpha	0.1715	2.2550	0.0245	
Beta	0.8945	45.2900	0.0000	2198.4630	Beta	0.8385	15.5200	0.0000	2032.3160

Table A5.2f: DCC correlation estimation equations between US and other markets

US and China	Parameter	T-value	T-probability	Log likelihood
Rho	0.0683	1.3880	0.1655	
Alpha	0.0237	1.2320	0.2185	
Beta	0.8678	11.5200	0.0000	4088.907
US and India	**Parameter**	**T-value**	**T-probability**	**Log likelihood**
Rho	0.3520	5.4920	0.0000	
Alpha	0.0230	0.5822	0.5606	4299.0600
Beta	0.9556	7.6900	0.0000	

Table A5.3a: Autocorrelation tests for means equations. Q-statistics on standardised residuals of African market and the US

US	Botswana
Q(5) = 5.26080 [0.3848883]	Q(5) = 0.520881 [0.9913387]
Q(10) = 11.4290 [0.3250827]	Q(10) = 2.20375 [0.9945265]
Q(20) = 27.3974 [0.1244494]	Q(20) = 12.7004 [0.8898673]
Q(50) = 67.1397 [0.0531693]	Q(50) = 41.6148 [0.7947121]
US	**Côte d'Ivoire**
Q(5) = 4.57916 [0.4693623]	Q(5) = 17.3491 [0.0038832]
Q(10) = 12.5002 [0.2529710]	Q(10) = 18.5153 [0.0468682]
Q(20) = 34.3065 [0.0241244]	Q(20) = 35.7862 [0.0162951]
Q(50) = 53.5348 [0.3402328]	Q(50) = 77.1545 [0.0081550]
US	**Egypt**
Q(5) = 2.89877 [0.7155884]	Q(5) = 8.58164 [0.1269602]
Q(10) = 6.84502 [0.7399904]	Q(10) = 9.93570 [0.4461529]
Q(20) = 18.0078 [0.5868919]	Q(20) = 14.2949 [0.8152334]
Q(50) = 49.4262 [0.4963313]	Q(50) = 45.2579 [0.6637883]
US	**Mauritius**
Q(5) = 3.91346 [0.5619417]	Q(5) = 15.3601 [0.0089296]
Q(10) = 12.8151 [0.2341942]	Q(10) = 21.8891 [0.0156796]
Q(20) = 29.9492 [0.0706815]	Q(20) = 37.0563 [0.0115213]
Q(50) = 91.2341 [0.0003317]	Q(50) = 70.0596 [0.0320297]
US	**Morocco**
Q(5) = 2.55929 [0.7675405]	Q(5) = 3.31089 [0.6521741]
Q(10) = 17.9268 [0.0562108]	Q(10) = 8.89133 [0.5424473]
Q(20) = 35.3134 [0.0184972]	Q(20) = 14.3984 [0.8097340]
Q(50) = 66.8350 [0.0559435]	Q(50) = 52.6462 [0.3720098]
US	**Namibia**
Q(5) = 8.44126 [0.1335353]	Q(5) = 12.5289 [0.0282171]
Q(10) = 17.6569 [0.0610336]	Q(10) = 14.2019 [0.1639782]
Q(20) = 35.3212 [0.0184589]	Q(20) = 20.4811 [0.4282181]
Q(50) = 70.8457 [0.0277818]	Q(50) = 35.2728 [0.9429700]
US	**Nigeria**
Q(5) = 10.8252 [0.0549587]	Q(5) = 1.16644 [0.9480560]
Q(10) = 17.8252 [0.0579850]	Q(10) = 6.60610 [0.7620339]
Q(20) = 33.7736 [0.0276974]	Q(20) = 15.7113 [0.7343684]
Q(50) = 58.6480 [0.1880083]	Q(50) = 56.1073 [0.2566915]

Table A5.3a: Continued

US	South Africa
Q(5) = 5.25194 [0.3859136]	Q(5) = 1.02278 [0.9607072]
Q(10) = 13.4045 [0.2019282]	Q(10) = 2.09706 [0.9955407]
Q(20) = 31.4739 [0.0492364]	Q(20) = 19.0184 [0.5206294]
Q(50) = 76.6870 [0.0089741]	Q(50) = 41.8406 [0.7873964]
US	**Tunisia**
Q(5) = 3.97539 [0.5529643]	Q(5) = 2.80520 [0.7299871]
Q(10) = 9.04335 [0.5279950]	Q(10) = 7.32283 [0.6946566]
Q(20) = 15.9177 [0.7217177]	Q(20) = 10.3743 [0.9608662]
Q(50) = 52.7812 [0.3670968]	Q(50) = 43.9660 [0.7129802]
US	**Zambia**
Q(5) = 2.51123 [0.7748034]	Q(5) = 0.222119 [0.9988572]
Q(10) = 5.58799 [0.8486098]	Q(10) = 3.10448 [0.9788571]
Q(20) = 25.3053 [0.1899989]	Q(20) = 20.2871 [0.4401065]
Q(50) = 50.6033 [0.4495668]	Q(50) = 50.5258 [0.4526120]

Table A5.3b: Autocorrelation tests for variance equations. Q-statistics on squared standardised residuals of African market and the US

US	Botswana
Q(5) = 2.40764 [0.7903359]	Q(5) = 3.37602 [0.6422254]
Q(10) = 10.1767 [0.4251262]	Q(10) = 3.87894 [0.9526429]
Q(20) = 17.7886 [0.6013336]	Q(20) = 6.67469 [0.9976235]
Q(50) = 38.4139 [0.8838511]	Q(50) = 25.5383 [0.9984199]
US	**Côte d'Ivoire**
Q(5) = 4.90710 [0.4273231]	Q(5) = 0.0202776 [0.9999969]
Q(10) = 15.3285 [0.1205371]	Q(10) = 0.0267572 [1.0000000]
Q(20) = 21.9265 [0.3445130]	Q(20) = 0.0659225 [1.0000000]
Q(50) = 54.5032 [0.3072301]	Q(50) = 0.233225 [1.0000000]
US	**Egypt**
Q(5) = 2.84593 [0.7237248]	Q(5) = 2.53422 [0.7713322]
Q(10) = 7.10729 [0.7152790]	Q(10) = 4.93576 [0.8954281]
Q(20) = 16.4673 [0.6872433]	Q(20) = 8.84869 [0.9845945]
Q(50) = 38.1741 [0.8893589]	Q(50) = 24.4731 [0.9991046]
US	**Mauritius**
Q(5) = 6.73748 [0.2409078]	Q(5) = 7.14116 [0.2103522]
Q(10) = 14.3275 [0.1585696]	Q(10) = 9.60947 [0.4753969]
Q(20) = 23.3689 [0.2710454]	Q(20) = 21.6651 [0.3589560]
Q(50) = 52.5205 [0.3766136]	Q(50) = 57.2934 [0.2228583]
US	**Morocco**
Q(5) = 3.60748 [0.6071901]	Q(5) = 4.64257 [0.4610373]
Q(10) = 13.2357 [0.2107896]	Q(10) = 11.5027 [0.3197192]
Q(20) = 23.6448 [0.2582540]	Q(20) = 19.8432 [0.4677788]
Q(50) = 42.3556 [0.7702489]	Q(50) = 50.1405 [0.4678213]

Table A5.3b: Continued

US	**Nigeria**
Q(5) = 6.38283 [0.2707295]	Q(5) = 5.42069 [0.3667206]
Q(10) = 12.1907 [0.2724940]	Q(10) = 7.36426 [0.6906670]
Q(20) = 25.5816 [0.1800790]	Q(20) = 19.4497 [0.4927937]
Q(50) = 49.9628 [0.4748773]	Q(50) = 45.0706 [0.6710632]
US	**South Africa**
Q(5) = 5.04171 [0.4108105]	Q(5) = 0.985591 [0.9637196]
Q(10) = 12.3202 [0.2641969]	Q(10) = 3.18107 [0.9768358]
Q(20) = 19.5393 [0.4870568]	Q(20) = 11.6620 [0.9272182]
Q(50) = 40.5193 [0.8283843]	Q(50) = 31.3861 [0.9817675]
US	**Tunisia**
Q(5) = 3.95023 [0.5566038]	Q(5) = 6.17467 [0.2895916]
Q(10) = 8.34486 [0.5951906]	Q(10) = 9.25366 [0.5082120]
Q(20) = 15.0080 [0.7759516]	Q(20) = 20.5269 [0.4254359]
Q(50) = 52.0350 [0.3946163]	Q(50) = 77.3824 [0.0077811]
US	**Zambia**
Q(5) = 8.22446 [0.1442913]	Q(5) = 1.75765 [0.8815583]
Q(10) = 14.3669 [0.1569046]	Q(10) = 3.58018 [0.9643056]
Q(20) = 24.1889 [0.2342382]	Q(20) = 5.76323 [0.9991815]
Q(50) = 59.7764 [0.1620587]	Q(50) = 16.9466 [0.9999968]

Table A5.3c: Autocorrelation tests for means equations. Q-statistics on standardised residuals of developed market and the US

US	Canada
Q(5) = 0.915652 [0.9690782]	Q(5) = 15.4686 [0.0085369]
Q(10) = 7.93783 [0.6349096]	Q(10) = 18.5531 [0.0463208]
Q(20) = 15.4668 [0.7491046]	Q(20) = 29.1675 [0.0845138]
Q(50) = 30.8346 [0.9849125]	Q(50) = 58.3329 [0.1957538]
US	**France**
Q(5) = 10.9619 [0.0521397]	Q(5) = 1.62664 [0.8980094]
Q(10) = 21.6589 [0.0169397]	Q(10) = 2.49436 [0.9909577]
Q(20) = 41.1486 [0.0035649]	Q(20) = 11.1333 [0.9426925]
Q(50) = 102.423 [0.0000179]	Q(50) = 46.1088 [0.6302537]
US	**Germany**
Q(5) = 5.11381 [0.4021492]	Q(5) = 2.27257 [0.8102870]
Q(10) = 13.7920 [0.1826907]	Q(10) = 5.00609 [0.8907709]
Q(20) = 23.2437 [0.2769870]	Q(20) = 10.9039 [0.9486770]
Q(50) = 55.8375 [0.2648162]	Q(50) = 28.7384 [0.9931656]
US	**Italy**
Q(5) = 3.48560 [0.6255672]	Q(5) = 3.21065 [0.6675468]
Q(10) = 8.79093 [0.5520535]	Q(10) = 6.24303 [0.7944483]
Q(20) = 21.1916 [0.3859355]	Q(20) = 13.7615 [0.8423775]
Q(50) = 59.2531 [0.1737483]	Q(50) = 39.1537 [0.8658006]
US	**Japan**
Q(5) = 5.94535 [0.3115732]	Q(5) = 7.53027 [0.1840943]
Q(10) = 12.2185 [0.2707013]	Q(10) = 11.9616 [0.2876363]
Q(20) = 24.4809 [0.2220158]	Q(20) = 28.3466 [0.1014458]
Q(50) = 41.9590 [0.7835081]	Q(50) = 55.3758 [0.2790737]
US	**Spain**
Q(5) = 8.58043 [0.1270158]	Q(5) = 0.729688 [0.9812997]
Q(10) = 24.3025 [0.0068366]	Q(10) = 4.67519 [0.9117934]
Q(20) = 49.3268 [0.0002763]	Q(20) = 17.0465 [0.6499551]
Q(50) = 98.9853 [0.0000453]	Q(50) = 51.9477 [0.3978900]
US	**UK**
Q(5) = 8.60988 [0.1256737]	Q(5) = 0.926784 [0.9682524]
Q(10) = 17.4110 [0.0657502]	Q(10) = 2.25366 [0.9940004]
Q(20) = 38.5984 [0.0074768]	Q(20) = 18.4902 [0.5551526]
Q(50) = 94.1615 [0.0001591]	Q(50) = 41.0870 [0.8113236]

Table A5.3d: Autocorrelation tests for variance equations. Q-statistics on squared standardised residuals of developed market and the US

US	**Canada**
Q(5) = 7.45330 [0.1890509]	Q(5) = 2.70258 [0.7457233]
Q(10) = 10.6254 [0.3874386]	Q(10) = 5.86004 [0.8268816]
Q(20) = 13.6688 [0.8468842]	Q(20) = 14.4113 [0.8090443]
Q(50) = 34.3051 [0.9557893]	Q(50) = 40.1648 [0.8385969]
US	**France**
Q(5) = 5.16117 [0.3965290]	Q(5) = 8.49440 [0.1310114]
Q(10) = 9.35252 [0.4990065]	Q(10) = 11.3745 [0.3290954]
Q(20) = 14.8640 [0.7841341]	Q(20) = 20.4503 [0.4300937]
Q(50) = 61.6599 [0.1247609]	Q(50) = 39.2824 [0.8625002]
US	**Germany**
Q(5) = 5.02590 [0.4127269]	Q(5) = 13.3569 [0.0202544]
Q(10) = 9.58778 [0.4773715]	Q(10) = 13.8064 [0.1820078]
Q(20) = 17.1976 [0.6401074]	Q(20) = 16.3288 [0.6960262]
Q(50) = 58.5049 [0.1914984]	Q(50) = 26.9606 [0.9968408]
US	**Italy**
Q(5) = 5.73410 [0.3329575]	Q(5) = 3.54180 [0.6170720]
Q(10) = 11.1430 [0.3464888]	Q(10) = 6.19362 [0.7987418]
Q(20) = 15.1207 [0.7694590]	Q(20) = 12.3010 [0.9053260]
Q(50) = 46.0860 [0.6311602]	Q(50) = 42.6730 [0.7593846]
US	**Japan**
Q(5) = 2.26591 [0.8112602]	Q(5) = 8.26937 [0.1420016]
Q(10) = 10.1458 [0.4277986]	Q(10) = 15.4515 [0.1164484]
Q(20) = 24.4623 [0.2227827]	Q(20) = 18.2395 [0.5716316]
Q(50) = 49.8337 [0.4800205]	Q(50) = 30.2194 [0.9878943]
US	**Spain**
Q(5) = 5.47041 [0.3612011]	Q(5) = 4.73851 [0.4486184]
Q(10) = 10.2578 [0.4181768]	Q(10) = 14.1572 [0.1659432]
Q(20) = 20.9266 [0.4014619]	Q(20) = 19.2096 [0.5082449]
Q(50) = 47.5400 [0.5726605]	Q(50) = 41.2525 [0.8061907]
US	**UK**
Q(5) = 5.13944 [0.3991010]	Q(5) = 4.75686 [0.4462680]
Q(10) = 8.06734 [0.6222591]	Q(10) = 10.0516 [0.4359779]
Q(20) = 14.9690 [0.7781790]	Q(20) = 19.3961 [0.4962317]
Q(50) = 49.1985 [0.5054920]	Q(50) = 40.1796 [0.8381789]

Table A5.3e: Autocorrelation tests for means equations. Q-statistics on standardised residuals of other markets and the US

US	China
Q(5) = 9.83559 [0.0800301]	Q(5) = 0.948898 [0.9665813]
Q(10) = 19.8350 [0.0308526]	Q(10) = 1.92671 [0.9968716]
Q(20) = 32.4469 [0.0387634]	Q(20) = 9.22055 [0.9802091]
Q(50) = 59.6496 [0.1648364]	Q(50) = 31.6082 [0.9803648]
US	**India**
Q(5) = 1.86501 [0.8674900]	Q(5) = 6.31611 [0.2766639]
Q(10) = 4.96216 [0.8936914]	Q(10) = 7.60988 [0.6668833]
Q(20) = 18.1800 [0.5755539]	Q(20) = 18.6893 [0.5420959]
Q(50) = 50.3844 [0.4581756]	Q(50) = 48.1118 [0.5494663]

Table A5.3f: Autocorrelation tests for variance equations. Q-statistics on squared standardised residuals of other markets and the US

US	China
Q(5) = 1.43493 [0.9204540]	Q(5) = 1.84445 [0.8702217]
Q(10) = 24.2375 [0.0069944]	Q(10) = 2.84079 [0.9849263]
Q(20) = 27.5678 [0.1200311]	Q(20) = 6.33046 [0.9983713]
Q(50) = 44.1838 [0.7048642]	Q(50) = 31.2628 [0.9825121]
US	**India**
Q(5) = 3.85390 [0.5706374]	Q(5) = 4.67241 [0.4571518]
Q(10) = 7.57587 [0.6701881]	Q(10) = 6.56112 [0.7661264]
Q(20) = 21.7843 [0.3523267]	Q(20) = 12.3466 [0.9036301]
Q(50) = 40.7235 [0.8223462]	Q(50) = 28.4155 [0.9940162]

Table A5.4a: Autocorrelation tests for means and variance equations. Hosking's tests on African markets

Hosking's multivariate portmanteau statistics on standardised residuals	Hosking's multivariate portmanteau statistics on squared standardised residuals
US and Botswana	**US and Botswana**
Hosking(5) = 7.73049 [0.9935059]	Hosking(5) = 20.0936 [0.3275740]
Hosking(10) = 22.2261 [0.9897213]	Hosking(10) = 43.0618 [0.2635508]
Hosking(20) = 64.3302 [0.8991563]	Hosking(20) = 71.2510 [0.6925084]
Hosking(50) = 222.485 [0.1318461]	Hosking(50) = 168.204 [0.9389269]
US and Côte d'Ivoire	**US and Côte d'Ivoire**
Hosking(5) = 30.9454 [0.0559158]	Hosking(5) = 7.51286 [0.9850415]
Hosking(10) = 61.3593 [0.0165030]	Hosking(10) = 29.8633 [0.8242656]
Hosking(20) = 122.389 [0.0016165]	Hosking(20) = 58.6087 [0.9504512]
Hosking(50) = 239.606 [0.0290002]	Hosking(50) = 145.645 [0.9979641]
US and Egypt	**US and Egypt**
Hosking(5) = 15.7874 [0.7297200]	Hosking(5) = 13.0079 [0.7911027]
Hosking(10) = 24.4498 [0.9748463]	Hosking(10) = 34.4234 [0.6355947]
Hosking(20) = 53.6290 [0.9897515]	Hosking(20) = 72.2722 [0.6615090]
Hosking(50) = 178.807 [0.8567689]	Hosking(50) = 186.516 [0.7105477]
US and Mauritius	**US and Mauritius**
Hosking(5) = 29.8764 [0.0718814]	Hosking(5) = 25.7104 [0.1065669]
Hosking(10) = 55.8860 [0.0488321]	Hosking(10) = 44.0118 [0.2321253]
Hosking(20) = 99.7156 [0.0670549]	Hosking(20) = 88.9666 [0.1859902]
Hosking(50) = 250.602 [0.0087451]	Hosking(50) = 207.364 [0.3096960]
US and Morocco	**US and Morocco**
Hosking(5) = 12.8661 [0.8830552]	Hosking(5) = 13.4916 [0.7615792]
Hosking(10) = 35.8023 [0.6596584]	Hosking(10) = 50.0211 [0.0917083]
Hosking(20) = 79.7731 [0.4861219]	Hosking(20) = 94.9168 [0.0934516]
Hosking(50) = 222.341 [0.1332821]	Hosking(50) = 213.249 [0.2174682]
US and Namibia	**US and Namibia**
Hosking(5) = 22.4132 [0.3185174]	Hosking(5) = 9.24651 [0.9537558]
Hosking(10) = 35.9088 [0.6549536]	Hosking(10) = 20.2936 [0.9917099]
Hosking(20) = 69.4172 [0.7948410]	Hosking(20) = 37.3238 [0.9999738]
Hosking(50) = 180.851 [0.8305238]	Hosking(50) = 80.3169 [1.0000000]
US and Nigeria	**US and Nigeria**
Hosking(5) = 13.3428 [0.8621956]	Hosking(5) = 23.7234 [0.1643005]
Hosking(10) = 29.6061 [0.8859086]	Hosking(10) = 37.0385 [0.5137650]
Hosking(20) = 63.2919 [0.9150104]	Hosking(20) = 81.8285 [0.3613549]
Hosking(50) = 192.941 [0.6269407]	Hosking(50) = 204.504 [0.3606500]

Table A5.4a: Continued

Hosking's multivariate portmanteau statistics on standardised residuals	Hosking's multivariate portmanteau statistics on squared standardised residuals
US and South Africa	**US and South Africa**
Hosking(5) = 9.95895 [0.9689102]	Hosking(5) = 31.1844 [0.0274049]
Hosking(10) = 24.4466 [0.9748756]	Hosking(10) = 52.5274 [0.0586731]
Hosking(20) = 72.7590 [0.7045566]	Hosking(20) = 93.4213 [0.1123429]
Hosking(50) = 195.169 [0.5832074]	Hosking(50) = 212.912 [0.2222485]
US and Tunisia	**US and Tunisia**
Hosking(5) = 17.1693 [0.6419539]	Hosking(5) = 32.4955 [0.0191949]
Hosking(10) = 36.8482 [0.6129298]	Hosking(10) = 58.8652 [0.0165351]
Hosking(20) = 53.6082 [0.9898103]	Hosking(20) = 103.345 [0.0290059]
Hosking(50) = 206.450 [0.3622852]	Hosking(50) = 264.546 [0.0011000]
US and Zambia	**US and Zambia**
Hosking(5) = 6.52454 [0.9979777]	Hosking(5) = 24.9917 [0.1251456]
Hosking(10) = 15.1584 [0.9998731]	Hosking(10) = 41.3778 [0.3254329]
Hosking(20) = 59.7450 [0.9560727]	Hosking(20) = 89.2904 [0.1797064]
Hosking(50) = 184.439 [0.7780535]	Hosking(50) = 180.868 [0.8032570]

Table A5.4b: Autocorrelation tests for means and variance equations. Hosking's tests on developed markets

Hosking's multivariate portmanteau statistics on standardised residuals	Hosking's multivariate portmanteau statistics on squared standardised residuals
US and Canada	**US and Canada**
Hosking(5) = 29.1976 [0.0839413]	Hosking(5) = 24.3528 [0.1438067]
Hosking(10) = 43.6117 [0.3204884]	Hosking(10) = 44.6457 [0.2125989]
Hosking(20) = 73.4057 [0.6855484]	Hosking(20) = 77.1736 [0.5051641]
Hosking(50) = 177.655 [0.8703658]	Hosking(50) = 183.023 [0.7699787]
US and France	**US and France**
Hosking(5) = 26.8318 [0.1400640]	Hosking(5) = 45.9707 [0.0002996]
Hosking(10) = 45.2604 [0.2617344]	Hosking(10) = 60.7260 [0.0110202]
Hosking(20) = 88.0636 [0.2515724]	Hosking(20) = 101.032 [0.0408658]
Hosking(50) = 245.362 [0.0158168]	Hosking(50) = 229.919 [0.0595943]
US and Germany	**US and Germany**
Hosking(5) = 15.9070 [0.7223750]	Hosking(5) = 58.1189 [0.0000041]
Hosking(10) = 34.6204 [0.7106449]	Hosking(10) = 68.0836 [0.0019422]
Hosking(20) = 65.6003 [0.8772478]	Hosking(20) = 95.2541 [0.0895597]
Hosking(50) = 197.491 [0.5368946]	Hosking(50) = 248.028 [0.0090955]
US and Italy	**US and Italy**
Hosking(5) = 14.2040 [0.8200020]	Hosking(5) = 31.6765 [0.0240067]
Hosking(10) = 31.5126 [0.8288881]	Hosking(10) = 44.8493 [0.2065754]
Hosking(20) = 70.9330 [0.7557149]	Hosking(20) = 80.0478 [0.4145586]
Hosking(50) = 182.466 [0.8078792]	Hosking(50) = 210.117 [0.2642587]
US and Japan	**US and Japan**
Hosking(5) = 21.0035 [0.3969285]	Hosking(5) = 22.5876 [0.2069378]
Hosking(10) = 45.5692 [0.2515251]	Hosking(10) = 67.7870 [0.0020908]
Hosking(20) = 100.450 [0.0607912]	Hosking(20) = 102.084 [0.0350333]
Hosking(50) = 225.357 [0.1054795]	Hosking(50) = 192.185 [0.6031601]
US and Spain	**US and Spain**
Hosking(5) = 19.6028 [0.4830069]	Hosking(5) = 40.0789 [0.0020362]
Hosking(10) = 45.2087 [0.2634711]	Hosking(10) = 64.8909 [0.0042272]
Hosking(20) = 103.443 [0.0400915]	Hosking(20) = 111.076 [0.0082547]
Hosking(50) = 252.234 [0.0072144]	Hosking(50) = 221.752 [0.1185761]
US and UK	**US and UK**
Hosking(5) = 17.9636 [0.5898058]	Hosking(5) = 46.2037 [0.0002770]
Hosking(10) = 32.7907 [0.7836206]	Hosking(10) = 62.3220 [0.0076943]
Hosking(20) = 88.4120 [0.2434202]	Hosking(20) = 95.8471 [0.0830321]
Hosking(50) = 242.093 [0.0224476]	Hosking(50) = 220.776 [0.1278580]

Table A5.4c: Autocorrelation tests for means and variance equations. Hosking's tests on other markets

Hosking's multivariate portmanteau statistics on standardised residuals	**Hosking's multivariate portmanteau statistics on squared standardised residuals**
US and China	**US and China**
Hosking(5) = 13.7185 [0.8444763]	Hosking(5) = 28.2733 [0.0580167]
Hosking(10) = 28.4267 [0.9144461]	Hosking(10) = 65.2399 [0.0038895]
Hosking(20) = 58.6097 [0.9653731]	Hosking(20) = 85.8073 [0.2551585]
Hosking(50) = 172.703 [0.9190412]	Hosking(50) = 186.855 [0.7044612]
US and India	**US and India**
Hosking(5) = 16.9293 [0.6575623]	Hosking(5) = 14.5173 [0.6948009]
Hosking(10) = 26.1611 [0.9551018]	Hosking(10) = 27.1301 [0.9052544]
Hosking(20) = 72.4443 [0.7136517]	Hosking(20) = 56.5791 [0.9677380]
Hosking(50) = 205.090 [0.3875840]	Hosking(50) = 199.069 [0.4652908]

Table A5.5a: Autocorrelation tests for means and variance equations. LM tests on African markets

Li and McLeod's multivariate portmanteau statistics on standardised residuals	Li and McLeod's multivariate portmanteau statistics on squared standardised residuals
US and Botswana	**US and Botswana**
Li-McLeod(5) = 7.78578 [0.9931928]	Li-McLeod(5) = 20.1218 [0.3260058]
Li-McLeod(10) = 22.3406 [0.9891896]	Li-McLeod(10) = 43.0705 [0.2632515]
Li-McLeod(20) = 64.3630 [0.8986263]	Li-McLeod(20) = 71.5448 [0.6836873]
Li-McLeod(50) = 220.747 [0.1499667]	Li-McLeod(50) = 170.014 [0.9257347]
US and Côte d'Ivoire	**US and Côte d'Ivoire**
Li-McLeod(5) = 30.9242 [0.0561995]	Li-McLeod(5) = 7.57278 [0.9843413]
Li-McLeod(10) = 61.2090 [0.0170315]	Li-McLeod(10) = 29.9278 [0.8220122]
Li-McLeod(20) = 121.703 [0.0018448]	Li-McLeod(20) = 58.8344 [0.9481705]
Li-McLeod(50) = 239.079 [0.0305820]	Li-McLeod(50) = 147.786 [0.9969361]
US and Egypt	**US and Egypt**
Li-McLeod(5) = 15.8466 [0.7260955]	Li-McLeod(5) = 13.0580 [0.7881153]
Li-McLeod(10) = 24.6809 [0.9726588]	Li-McLeod(10) = 34.4203 [0.6357370]
Li-McLeod(20) = 54.1312 [0.9882517]	Li-McLeod(20) = 72.3644 [0.6586661]
Li-McLeod(50) = 179.256 [0.8512341]	Li-McLeod(50) = 186.177 [0.7165755]
US and Mauritius	**Mauritius**
Li-McLeod(5) = 29.8601 [0.0721517]	Li-McLeod(5) = 25.6815 [0.1072660]
Li-McLeod(10) = 55.7938 [0.0496737]	Li-McLeod(10) = 43.9861 [0.2329389]
Li-McLeod(20) = 99.6172 [0.0679324]	Li-McLeod(20) = 88.8009 [0.1892645]
Li-McLeod(50) = 248.257 [0.0114548]	Li-McLeod(50) = 207.310 [0.3106251]
US and Morocco	**US and Morocco**
Li-McLeod(5) = 12.8956 [0.8818169]	Li-McLeod(5) = 13.5321 [0.7590469]
Li-McLeod(10) = 35.7962 [0.6599233]	Li-McLeod(10) = 49.8621 [0.0942388]
Li-McLeod(20) = 79.6846 [0.4889152]	Li-McLeod(20) = 94.6392 [0.0967541]
Li-McLeod(50) = 221.436 [0.1425811]	Li-McLeod(50) = 212.743 [0.2246552]
US and Namibia	**US and Namibia**
Li-McLeod(5) = 22.4414 [0.3170490]	Li-McLeod(5) = 9.30245 [0.9523192]
Li-McLeod(10) = 36.0230 [0.6498947]	Li-McLeod(10) = 20.4393 [0.9911134]
Li-McLeod(20) = 69.6879 [0.7880980]	Li-McLeod(20) = 38.0276 [0.9999612]
Li-McLeod(50) = 181.450 [0.8223171]	Li-McLeod(50) = 85.1658 [1.0000000]
US and Nigeria	**US and Nigeria**
Li-McLeod(5) = 13.3808 [0.8604525]	Li-McLeod(5) = 23.7290 [0.1641086]
Li-McLeod(10) = 29.6795 [0.8839598]	Li-McLeod(10) = 37.1347 [0.5092994]
Li-McLeod(20) = 63.5395 [0.9113958]	Li-McLeod(20) = 81.8123 [0.3618246]
Li-McLeod(50) = 192.868 [0.6283499]	Li-McLeod(50) = 204.227 [0.3657623]

Table A5.5a: Continued

Li and McLeod's multivariate portmanteau statistics on standardised residuals	Li and McLeod's multivariate portmanteau statistics on squared standardised residuals
US and South Africa	**US and South Africa**
Li-McLeod(5) = 10.0058 [0.9680658]	Li-McLeod(5) = 31.1710 [0.0275030]
Li-McLeod(10) = 24.5567 [0.9738522]	Li-McLeod(10) = 52.5106 [0.0588549]
Li-McLeod(20) = 72.6273 [0.7083753]	Li-McLeod(20) = 93.4676 [0.1117163]
Li-McLeod(50) = 195.112 [0.5843370]	Li-McLeod(50) = 213.271 [0.2171684]
US and Tunisia	**US and Tunisia**
Li-McLeod(5) = 17.1893 [0.6406514]	Li-McLeod(5) = 32.4723 [0.0193179]
Li-McLeod(10) = 36.8741 [0.6117615]	Li-McLeod(10) = 58.7656 [0.0168913]
Li-McLeod(20) = 54.1925 [0.9880569]	Li-McLeod(20) = 103.225 [0.0295382]
Li-McLeod(50) = 205.304 [0.3835523]	Li-McLeod(50) = 261.949 [0.0015700]
US and Zambia	**US and Zambia**
Li-McLeod(5) = 6.58288 [0.9978455]	Li-McLeod(5) = 24.9907 [0.1251713]
Li-McLeod(10) = 15.3530 [0.9998504]	Li-McLeod(10) = 41.4265 [0.3235386]
Li-McLeod(20) = 59.9013 [0.9546575]	Li-McLeod(20) = 89.1451 [0.1825073]
Li-McLeod(50) = 184.415 [0.7784322]	Li-McLeod(50) = 182.217 [0.7827406]

Table A5.5b: Autocorrelation tests for means and variance equations. LM tests on developed markets

Li and McLeod's multivariate portmanteau statistics on standardised residuals	Li and McLeod's multivariate portmanteau statistics on squared standardised residuals
US and Canada	**US and Canada**
Li-McLeod(5) = 29.1360 [0.0851162]	Li-McLeod(5) = 24.3776 [0.1430421]
Li-McLeod(10) = 43.6088 [0.3205996]	Li-McLeod(10) = 44.6673 [0.2119534]
Li-McLeod(20) = 73.6505 [0.6782515]	Li-McLeod(20) = 77.4193 [0.4972735]
Li-McLeod(50) = 178.874 [0.8559573]	Li-McLeod(50) = 183.818 [0.7570192]
US and France	**US and France**
Li-McLeod(5) = 26.8100 [0.1406956]	Li-McLeod(5) = 45.8748 [0.0003094]
Li-McLeod(10) = 45.2635 [0.2616321]	Li-McLeod(10) = 60.6765 [0.0111419]
Li-McLeod(20) = 88.1050 [0.2505960]	Li-McLeod(20) = 101.048 [0.0407685]
Li-McLeod(50) = 243.086 [0.0202163]	Li-McLeod(50) = 229.434 [0.0622576]
US and Germany	**US and Germany**
Li-McLeod(5) = 15.9269 [0.7211507]	Li-McLeod(5) = 58.0796 [0.0000042]
Li-McLeod(10) = 34.6525 [0.7092917]	Li-McLeod(10) = 68.1557 [0.0019076]
Li-McLeod(20) = 65.8269 [0.8730461]	Li-McLeod(20) = 95.6821 [0.0848093]
Li-McLeod(50) = 196.735 [0.5520164]	Li-McLeod(50) = 246.451 [0.0109157]
US and Italy	**US and Italy**
Li-McLeod(5) = 14.2377 [0.8182419]	Li-McLeod(5) = 31.6565 [0.0241366]
Li-McLeod(10) = 31.5857 [0.8264436]	Li-McLeod(10) = 44.9063 [0.2049104]
Li-McLeod(20) = 71.0590 [0.7523164]	Li-McLeod(20) = 80.2730 [0.4076766]
Li-McLeod(50) = 183.141 [0.7979475]	Li-McLeod(50) = 209.757 [0.2699804]
US and Japan	**US and Japan**
Li-McLeod(5) = 21.0058 [0.3967922]	Li-McLeod(5) = 22.5782 [0.2073223]
Li-McLeod(10) = 45.5077 [0.2535380]	Li-McLeod(10) = 67.4077 [0.0022965]
Li-McLeod(20) = 99.9366 [0.0651175]	Li-McLeod(20) = 101.823 [0.0364086]
Li-McLeod(50) = 224.321 [0.1144923]	Li-McLeod(50) = 193.487 [0.5772953]
US and Spain	**US and Spain**
Li-McLeod(5) = 19.6105 [0.4825212]	Li-McLeod(5) = 40.0142 [0.0020780]
Li-McLeod(10) = 45.1530 [0.2653466]	Li-McLeod(10) = 64.7683 [0.0043523]
Li-McLeod(20) = 103.089 [0.0421765]	Li-McLeod(20) = 110.880 [0.0085381]
Li-McLeod(50) = 250.057 [0.0093171]	Li-McLeod(50) = 222.080 [0.1155762]
US and UK	**US and UK**
Li-McLeod(5) = 17.9763 [0.5889711]	Li-McLeod(5) = 46.0871 [0.0002881]
Li-McLeod(10) = 32.8756 [0.7804300]	Li-McLeod(10) = 62.2541 [0.0078144]
Li-McLeod(20) = 88.1857 [0.2486970]	Li-McLeod(20) = 95.9771 [0.0816541]
Li-McLeod(50) = 239.908 [0.0281260]	Li-McLeod(50) = 220.494 [0.1306326]

Table A5.5c: Autocorrelation tests for means and variance equations. LM tests on other markets

Li and McLeod's multivariate portmanteau statistics on standardised residuals	**Li and McLeod's multivariate portmanteau statistics on squared standardised residuals**
US and China	**US and China**
Li-McLeod(5) = 13.7467 [0.8431025]	Li-McLeod(5) = 28.2492 [0.0583627]
Li-McLeod(10) = 28.5272 [0.9122165]	Li-McLeod(10) = 64.9959 [0.0041229]
Li-McLeod(20) = 58.9036 [0.9631248]	Li-McLeod(20) = 86.0434 [0.2495009]
Li-McLeod(50) = 173.119 [0.9155490]	Li-McLeod(50) = 188.106 [0.6815600]
US and India	**US and India**
Li-McLeod(5) = 16.9570 [0.6557610]	Li-McLeod(5) = 14.5398 [0.6932844]
Li-McLeod(10) = 26.3272 [0.9527176]	Li-McLeod(10) = 27.2440 [0.9024650]
Li-McLeod(20) = 72.4721 [0.7128520]	Li-McLeod(20) = 56.9463 [0.9650169]
Li-McLeod(50) = 204.620 [0.3964545]	Li-McLeod(50) = 197.780 [0.4910474]

Figure A5.1: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Botswana and US

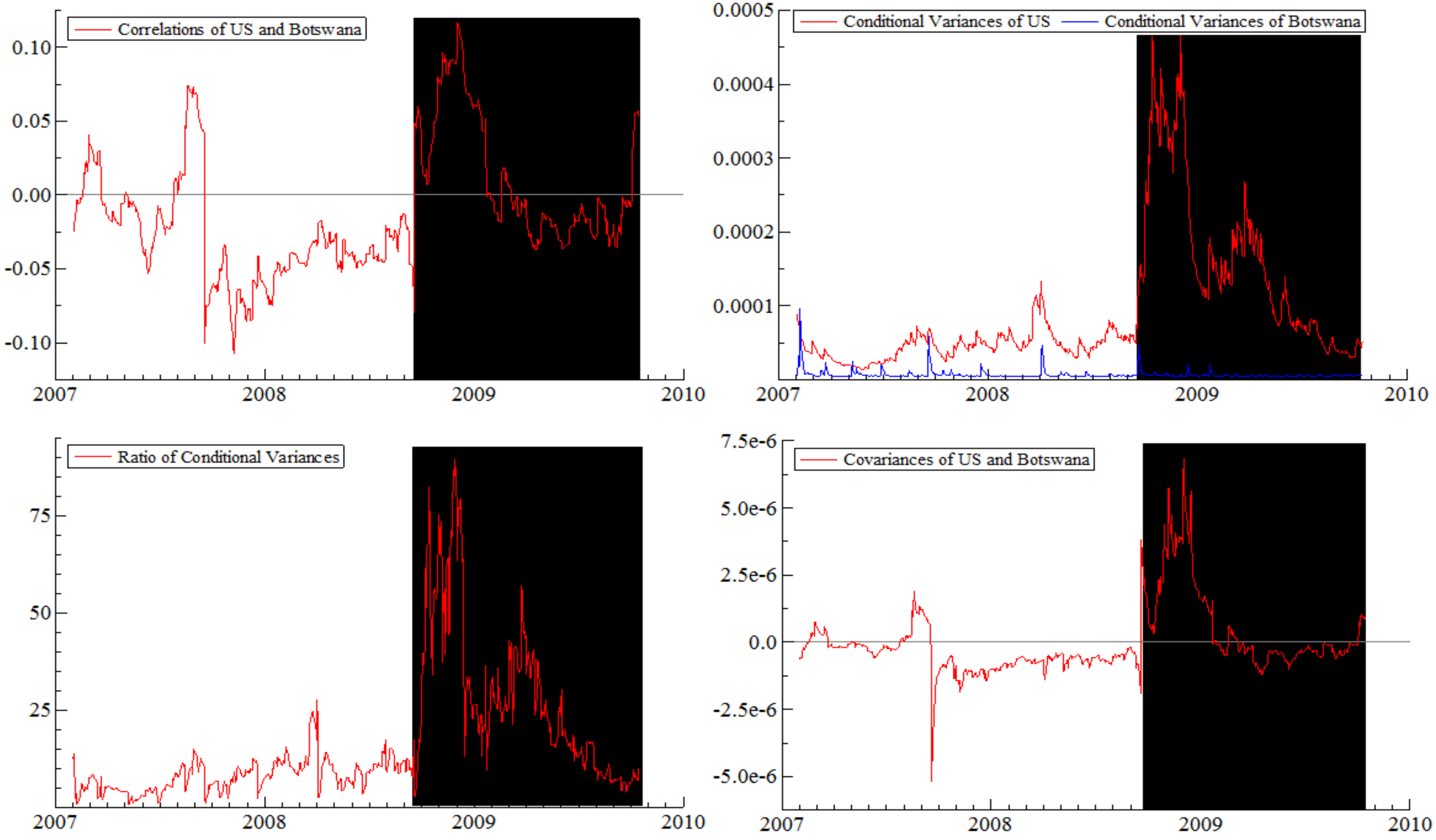


Figure A5.2: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Côte d'Ivoire and the US

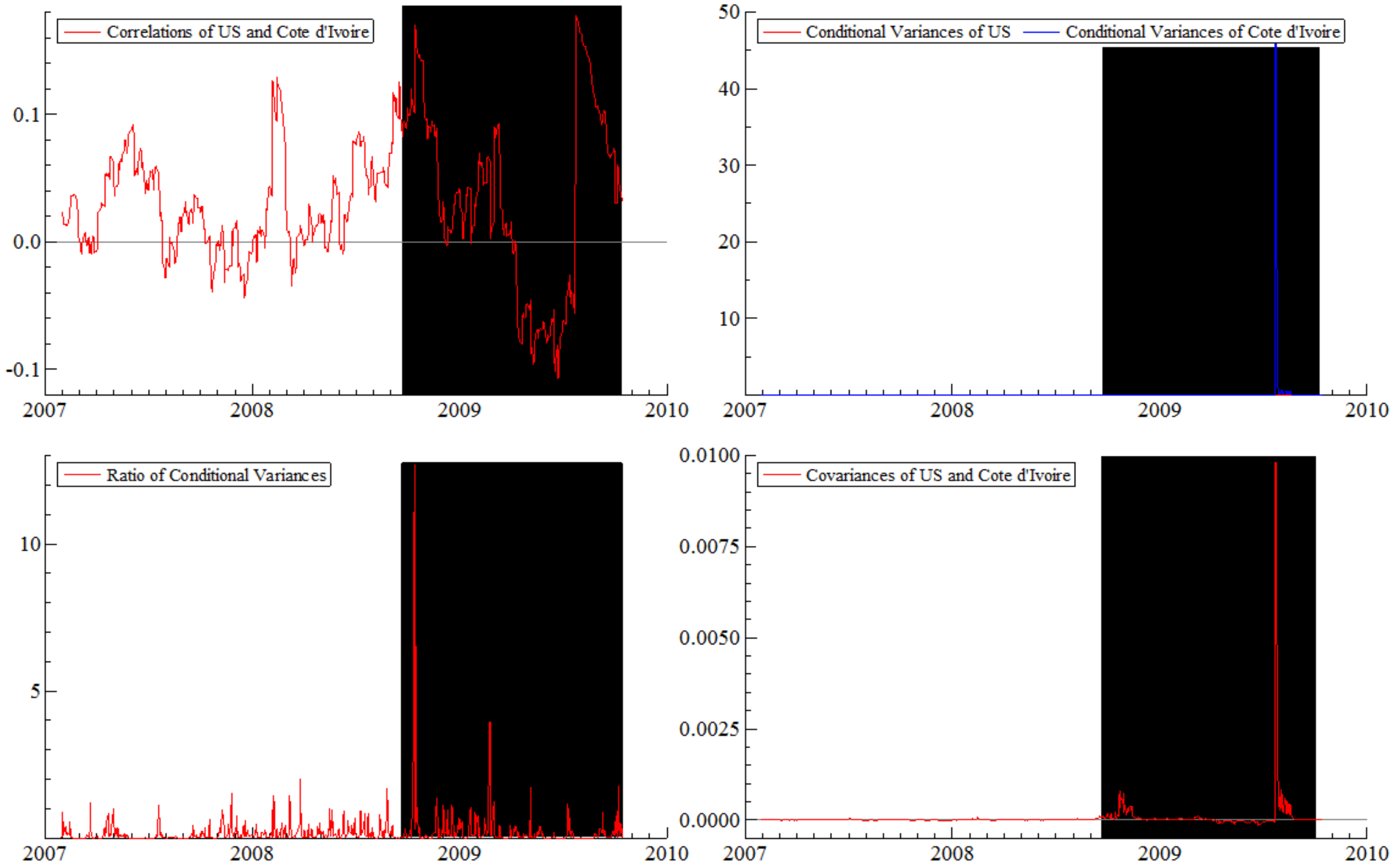


Figure A5.3: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Egypt and US

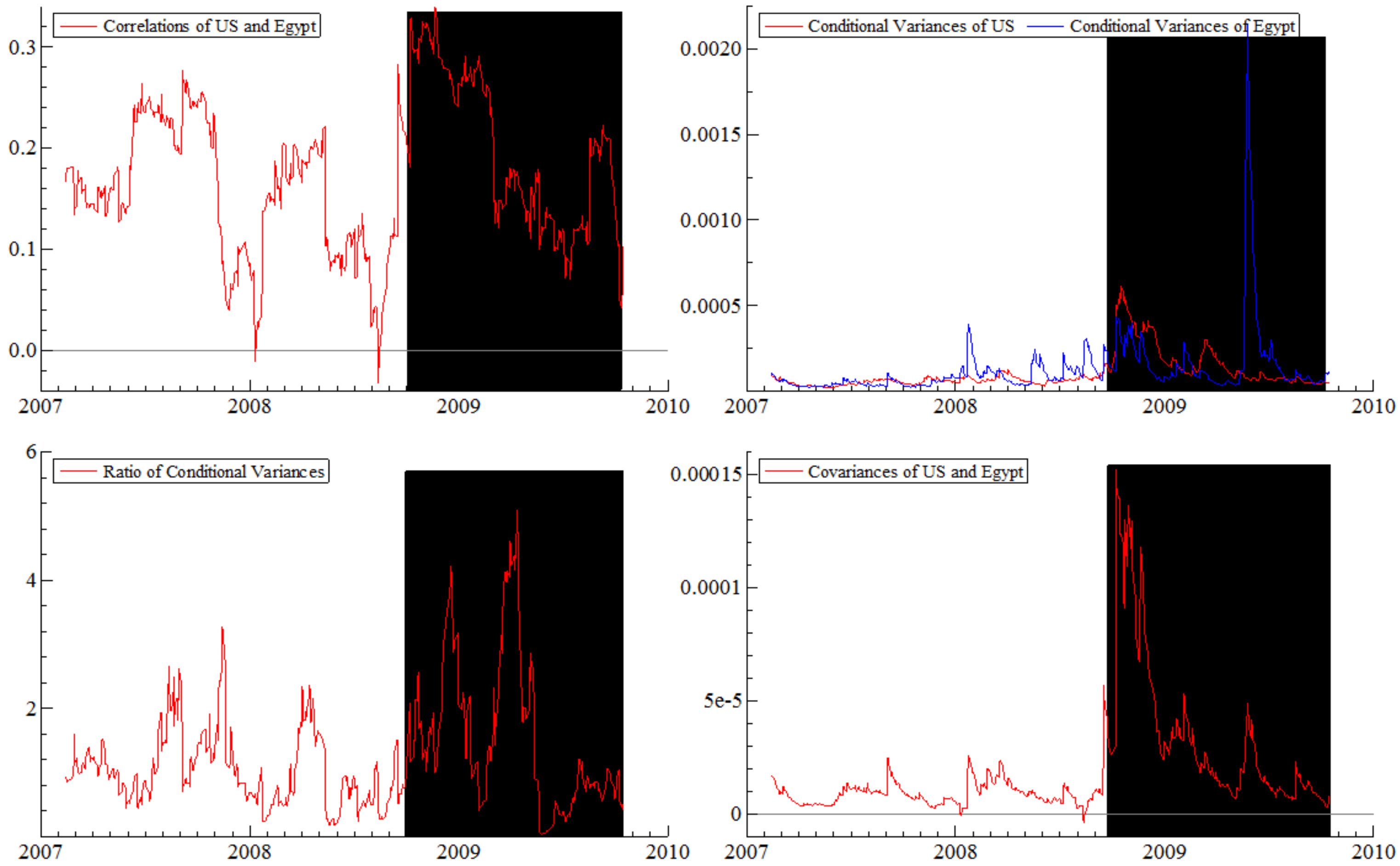


Figure A5.4: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Mauritius and US

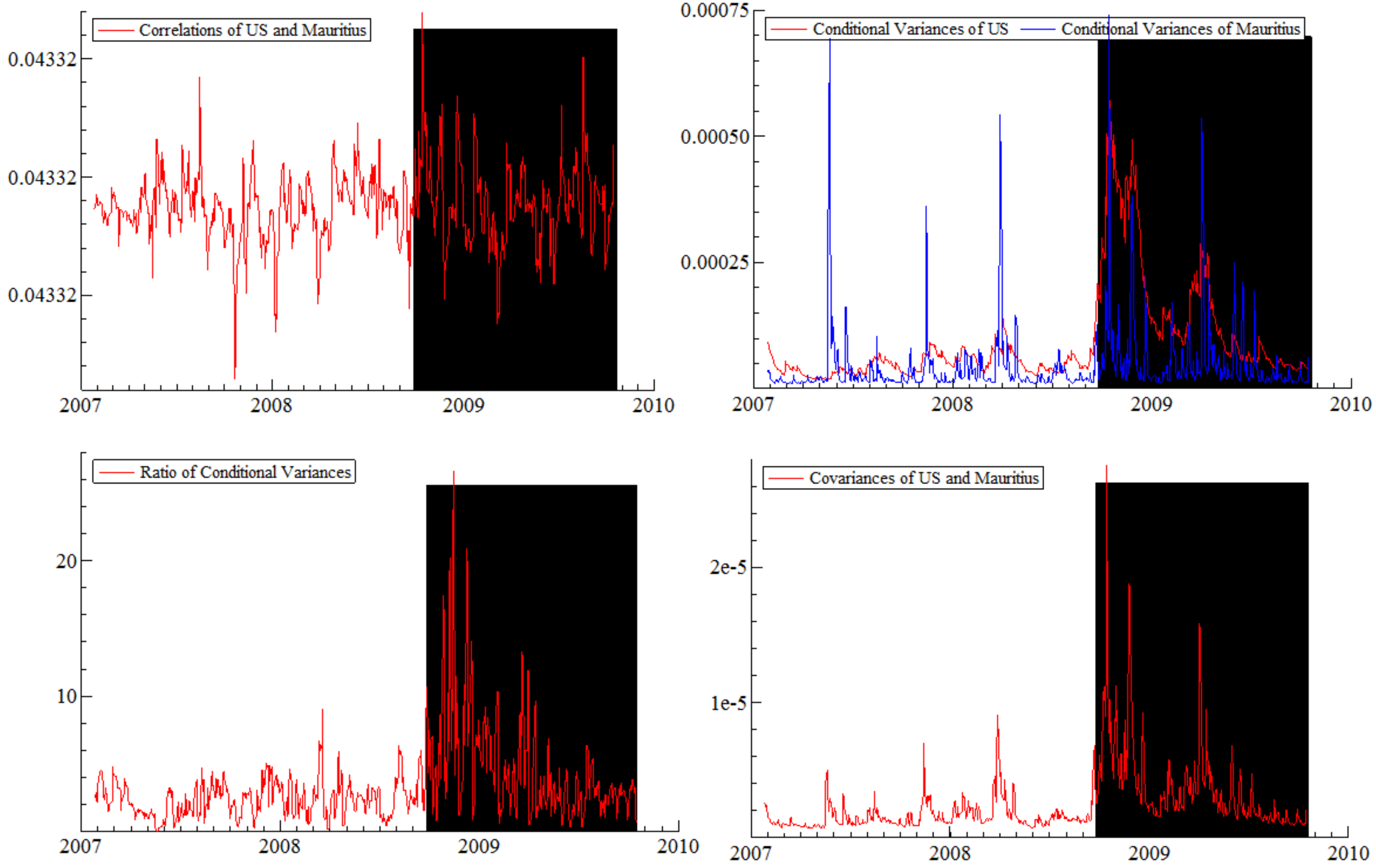


Figure A5.5: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Morocco and US

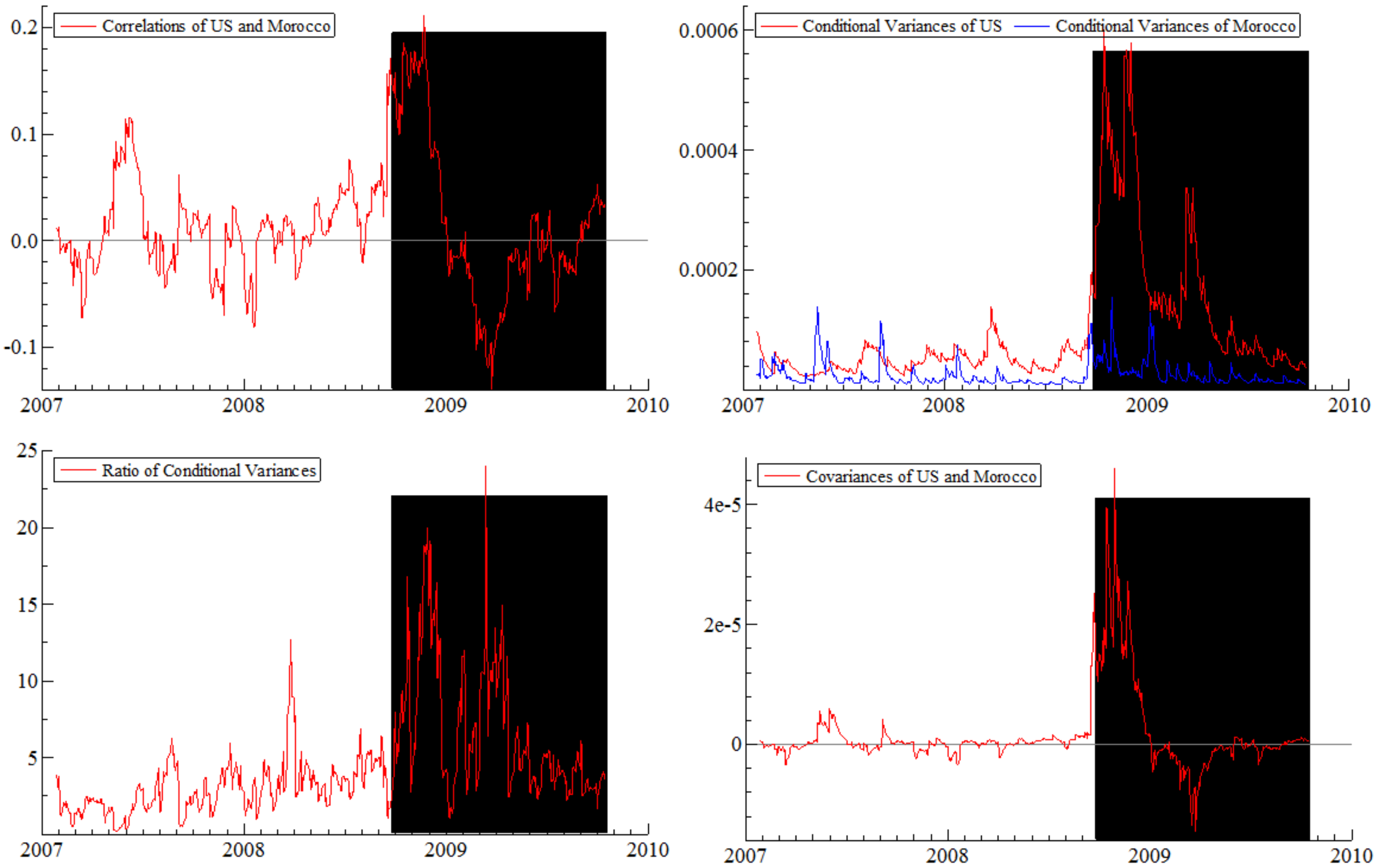


Figure A5.6: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Namibia and US

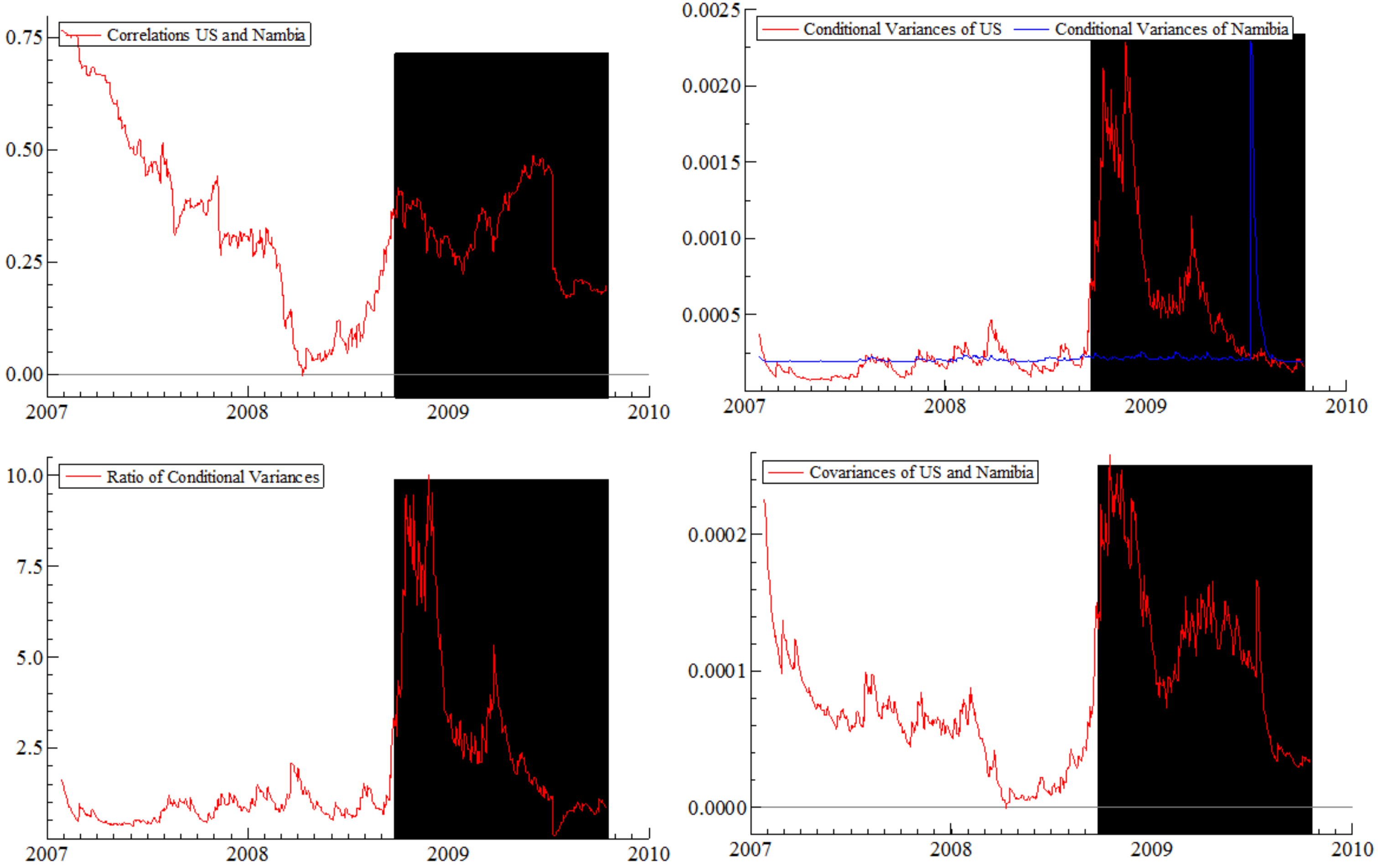


Figure A5.7: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Nigeria and US

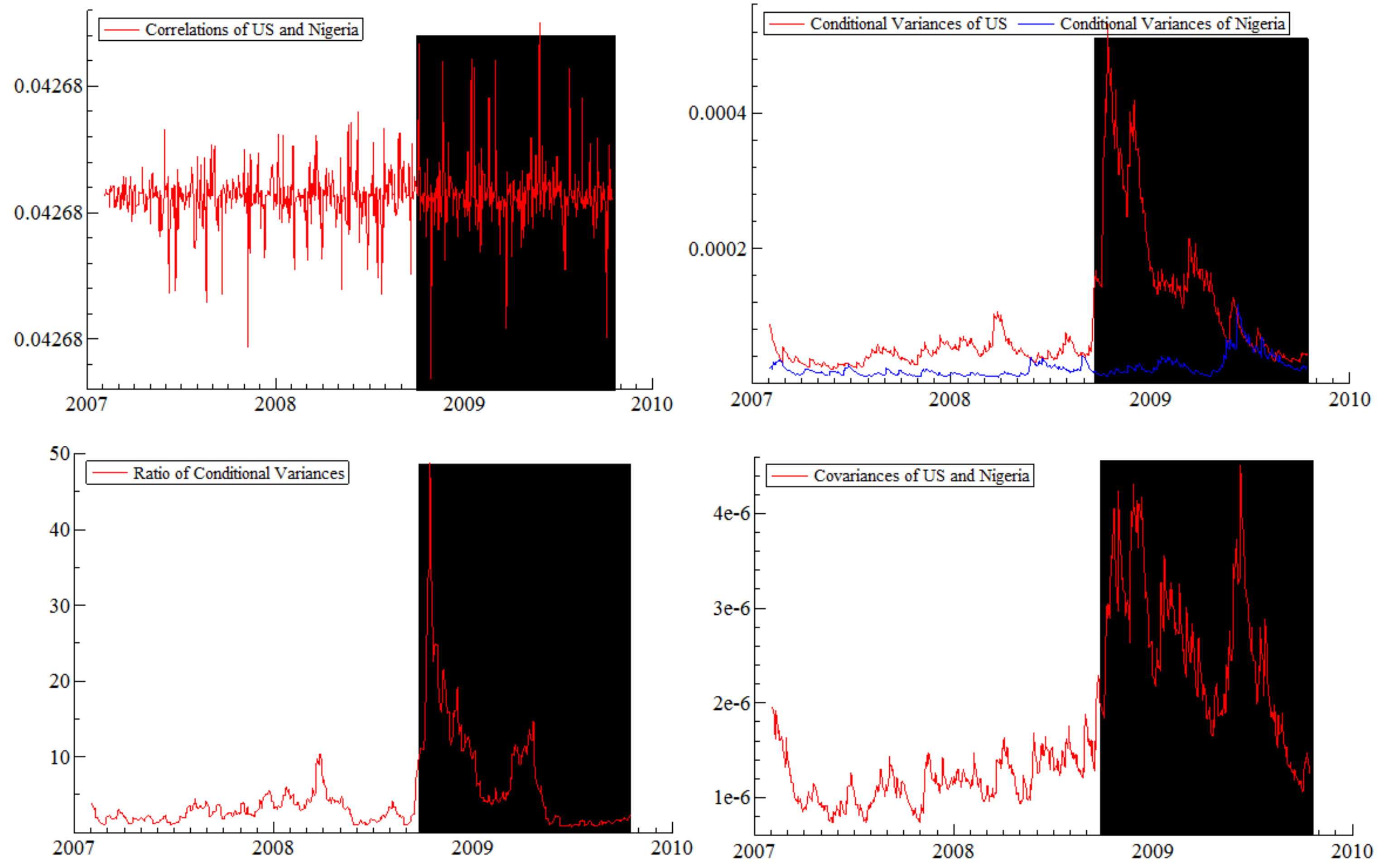


Figure A5.8: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of South Africa and US

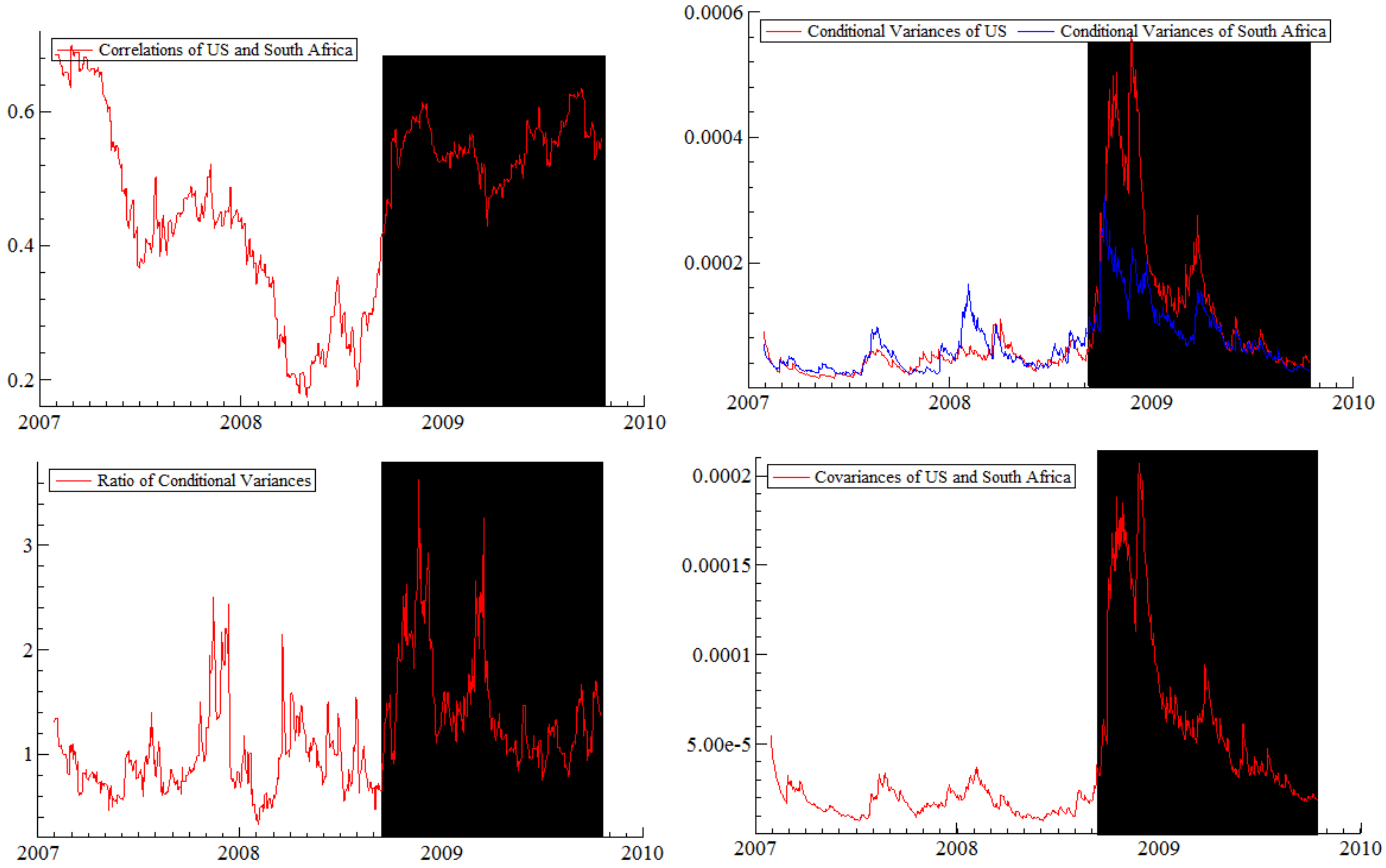


Figure A5.9: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Tunisia and US

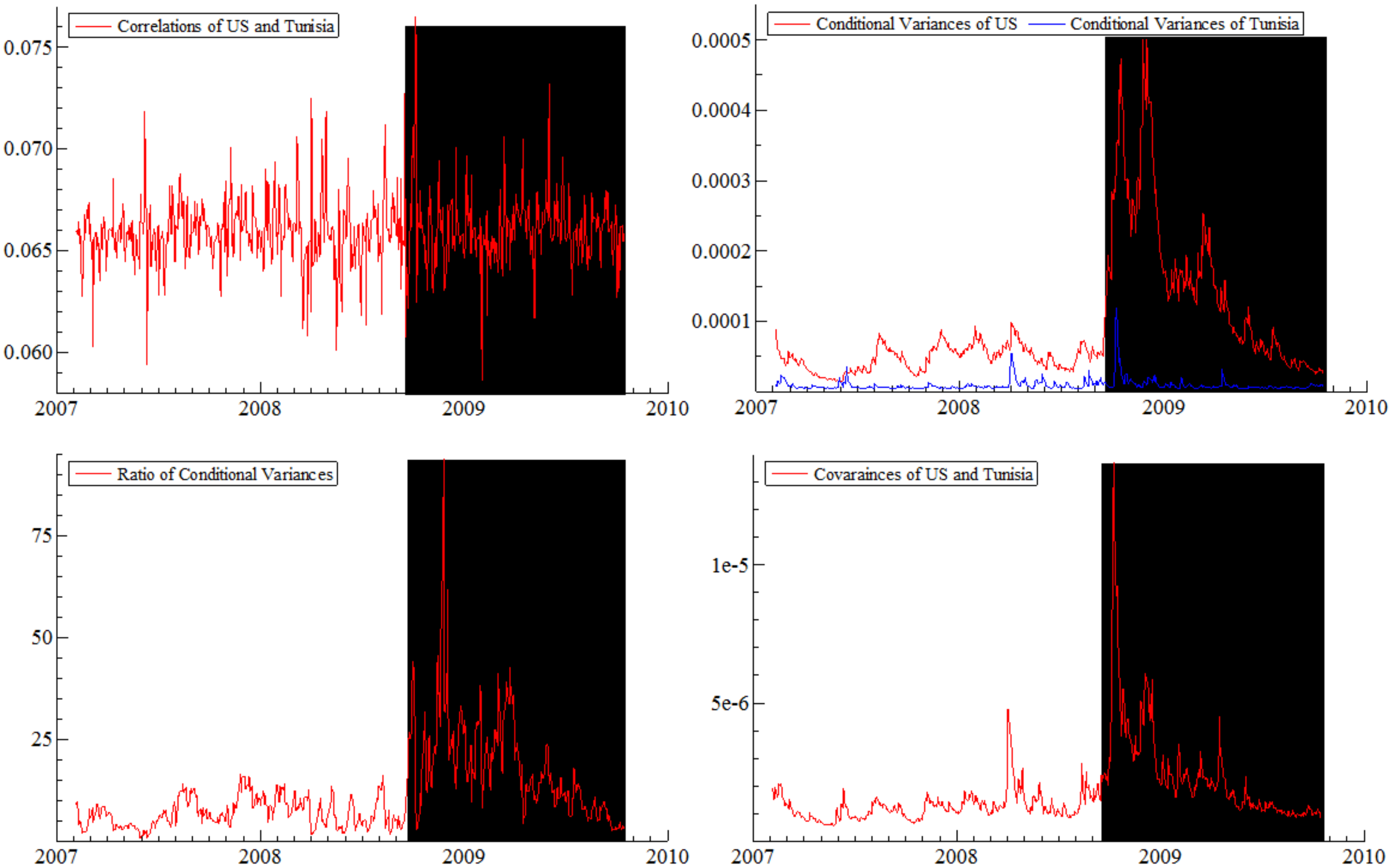


Figure A5.10: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Zambia and US

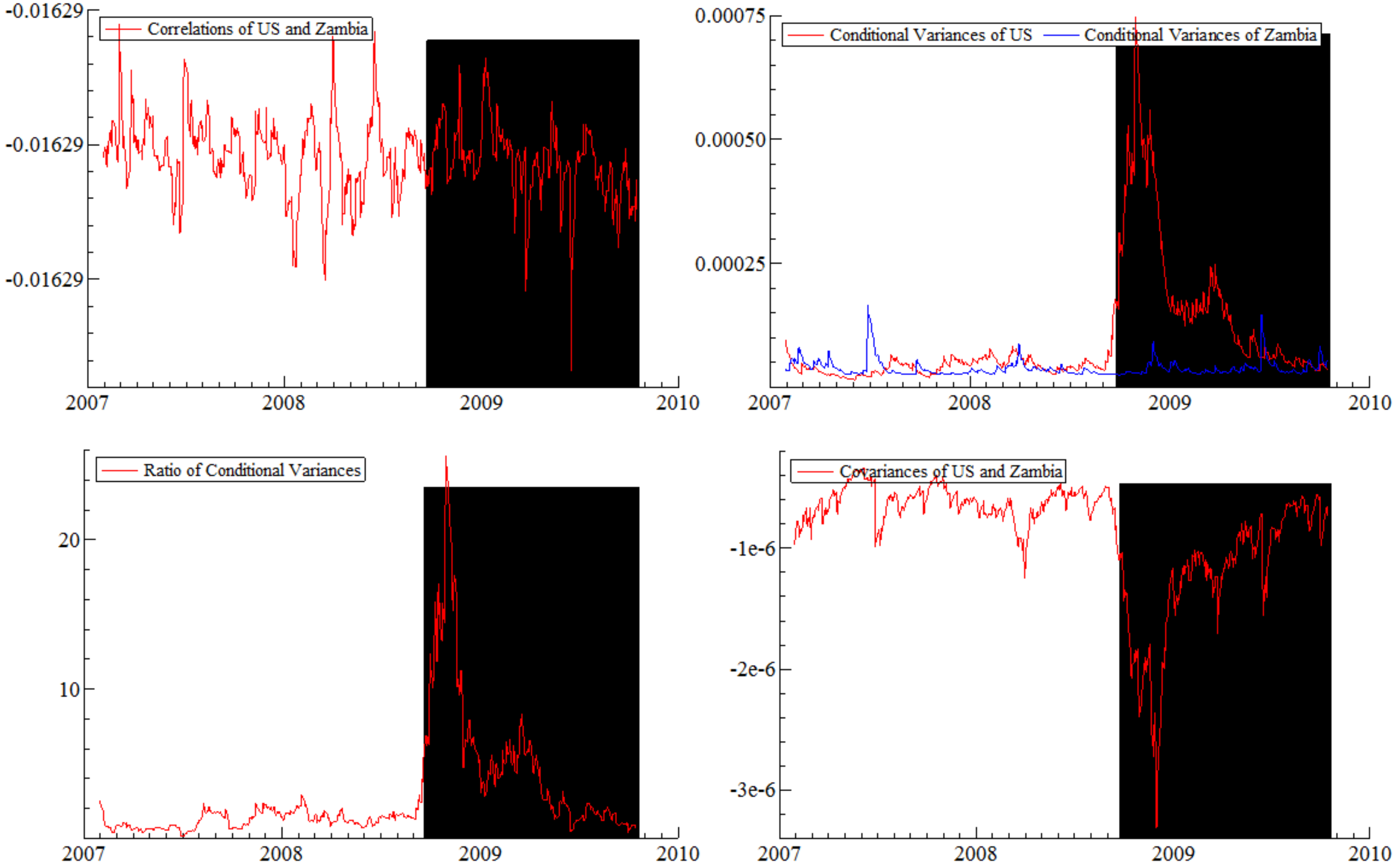


Figure A5.11: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Canada and US

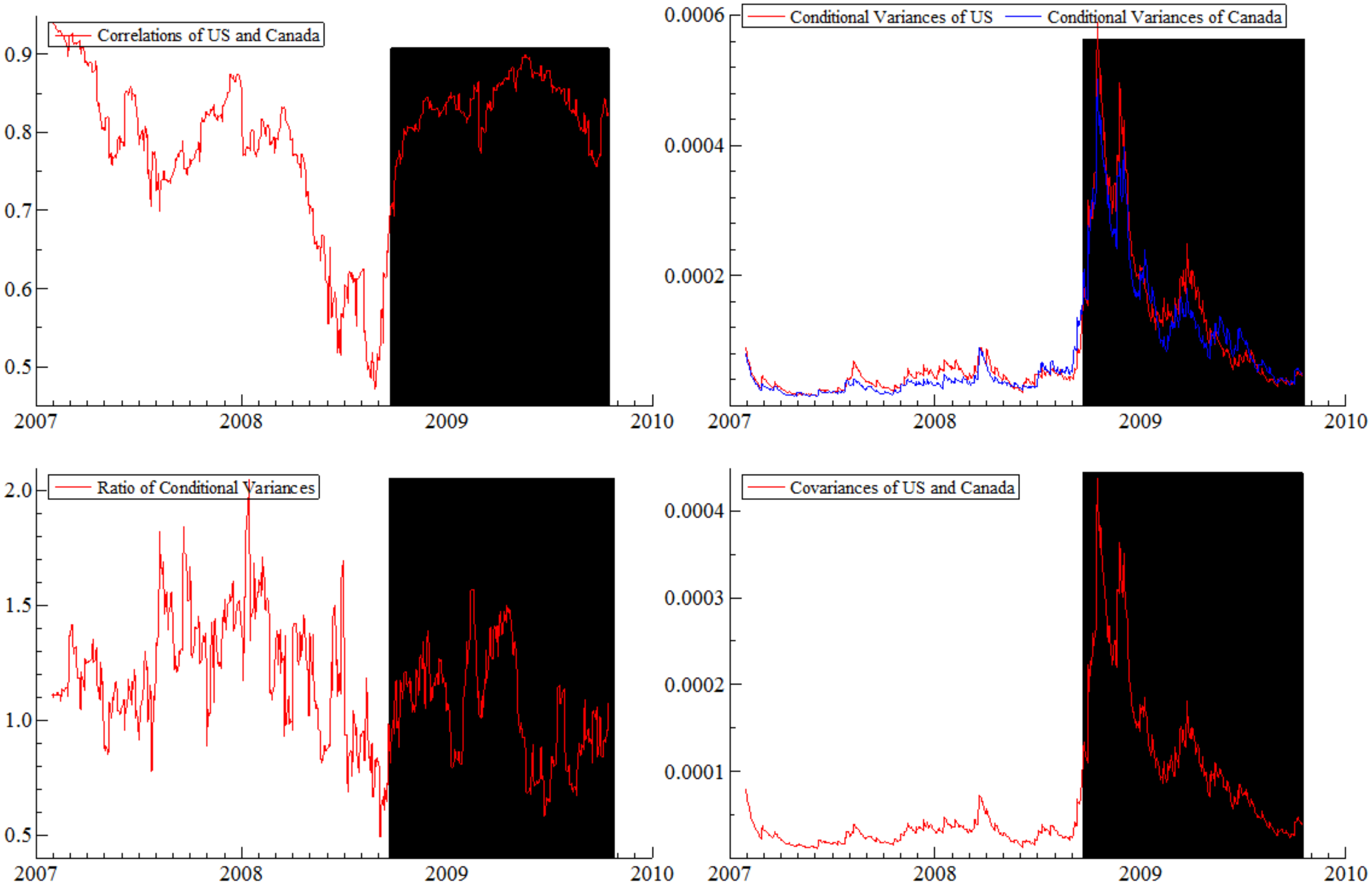


Figure A5.12: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of France and US

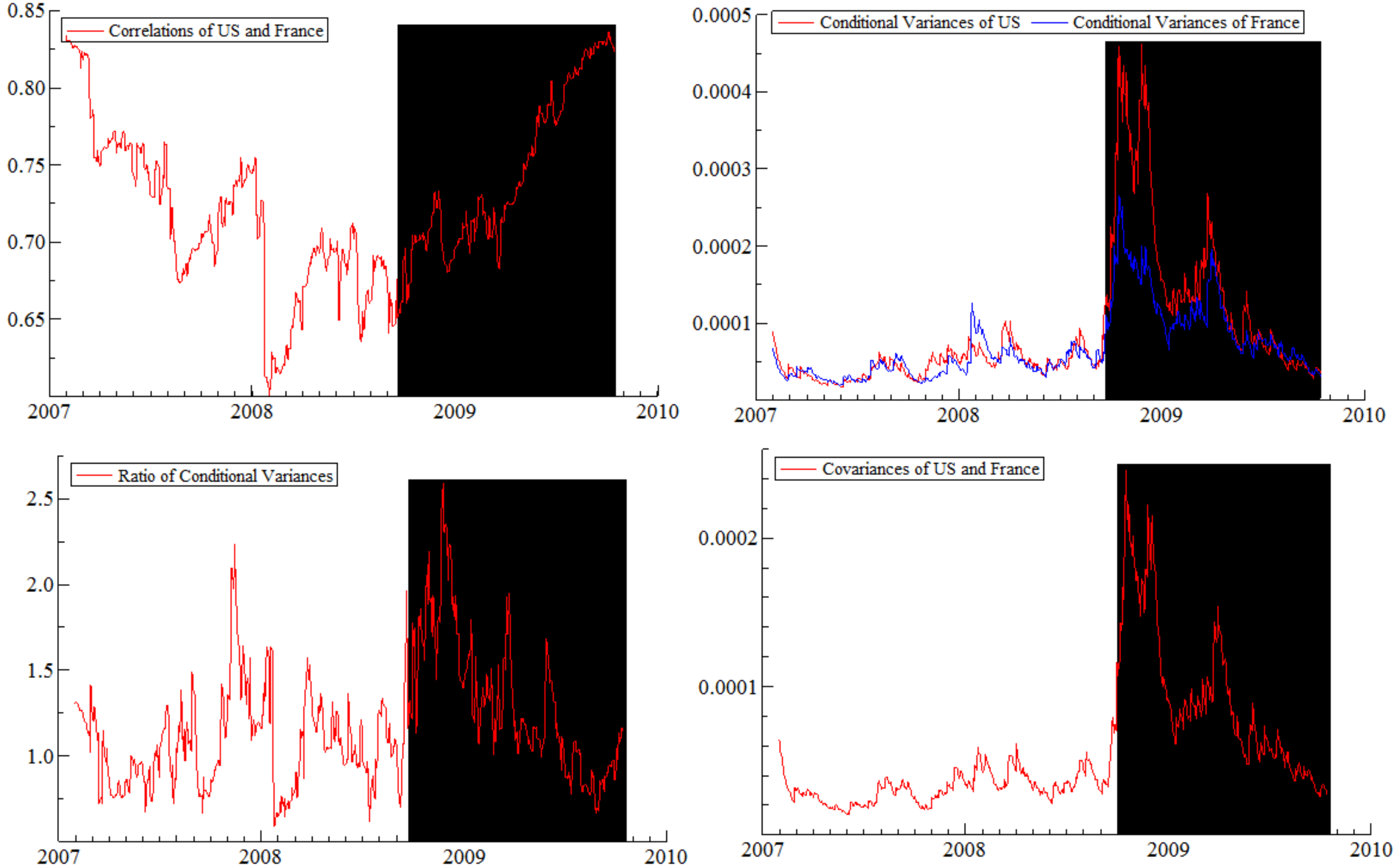


Figure A5.13: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Germany and US

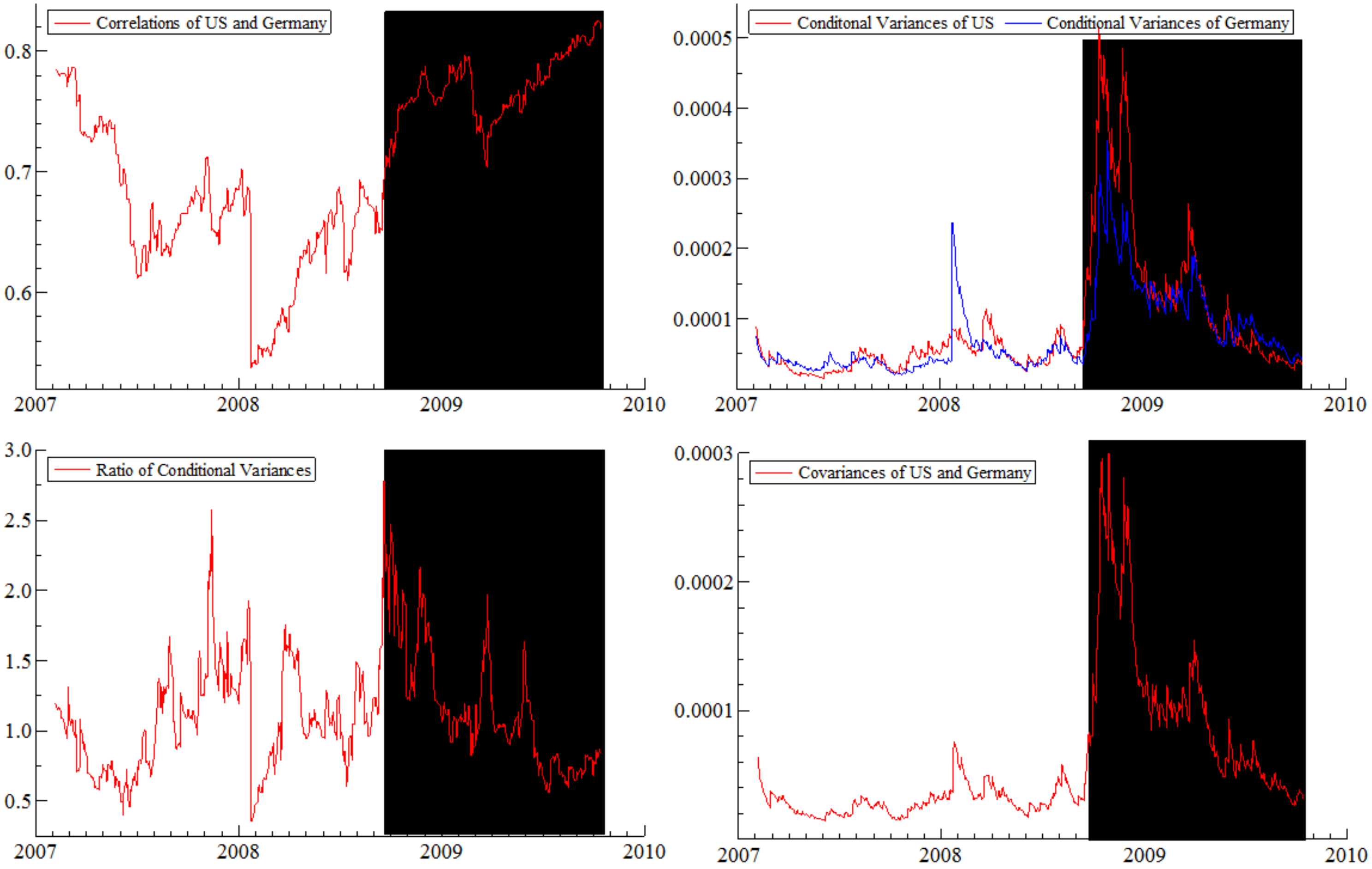


Figure A5.14: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Italy and US

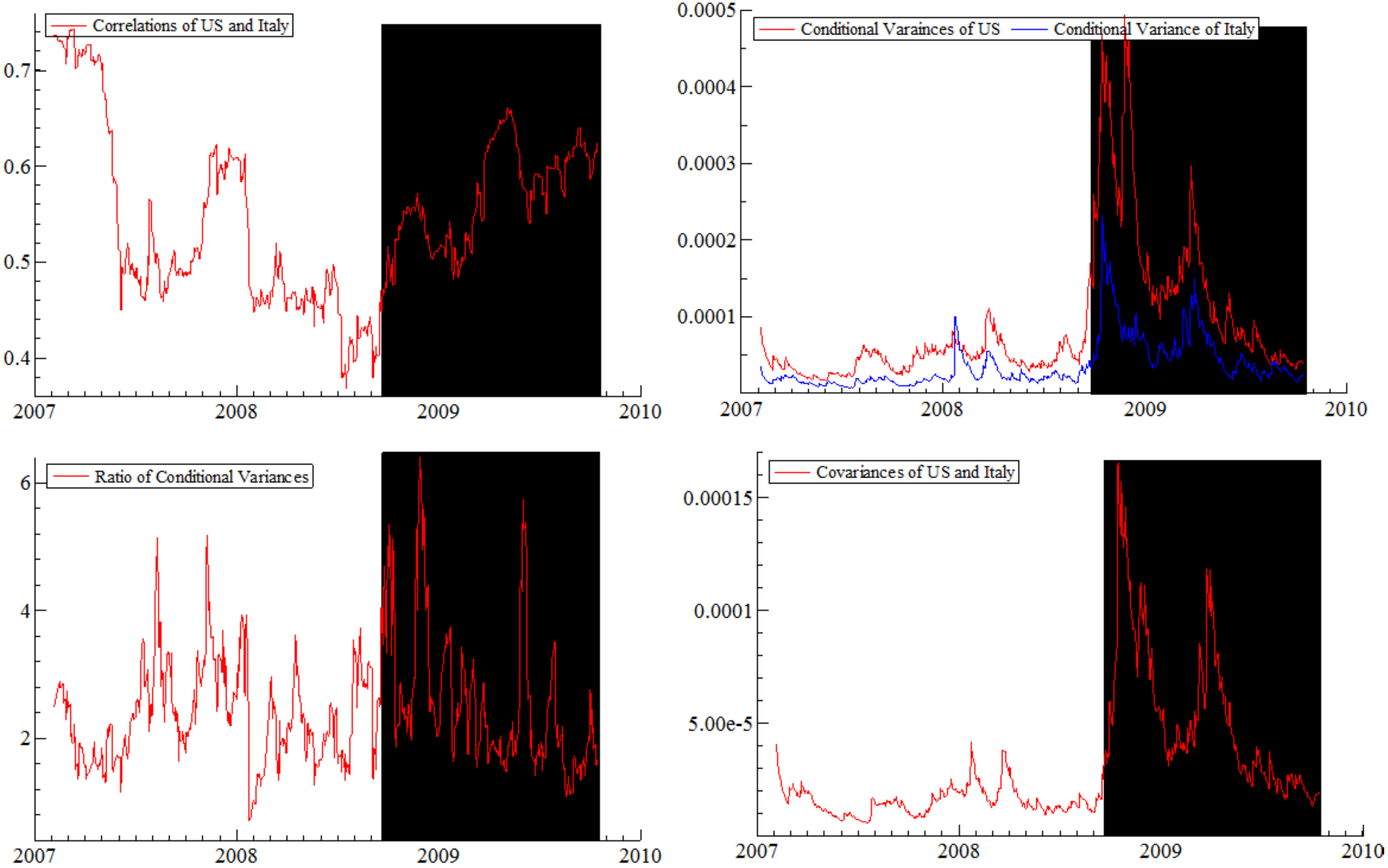


Figure A5.15: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Japan and US

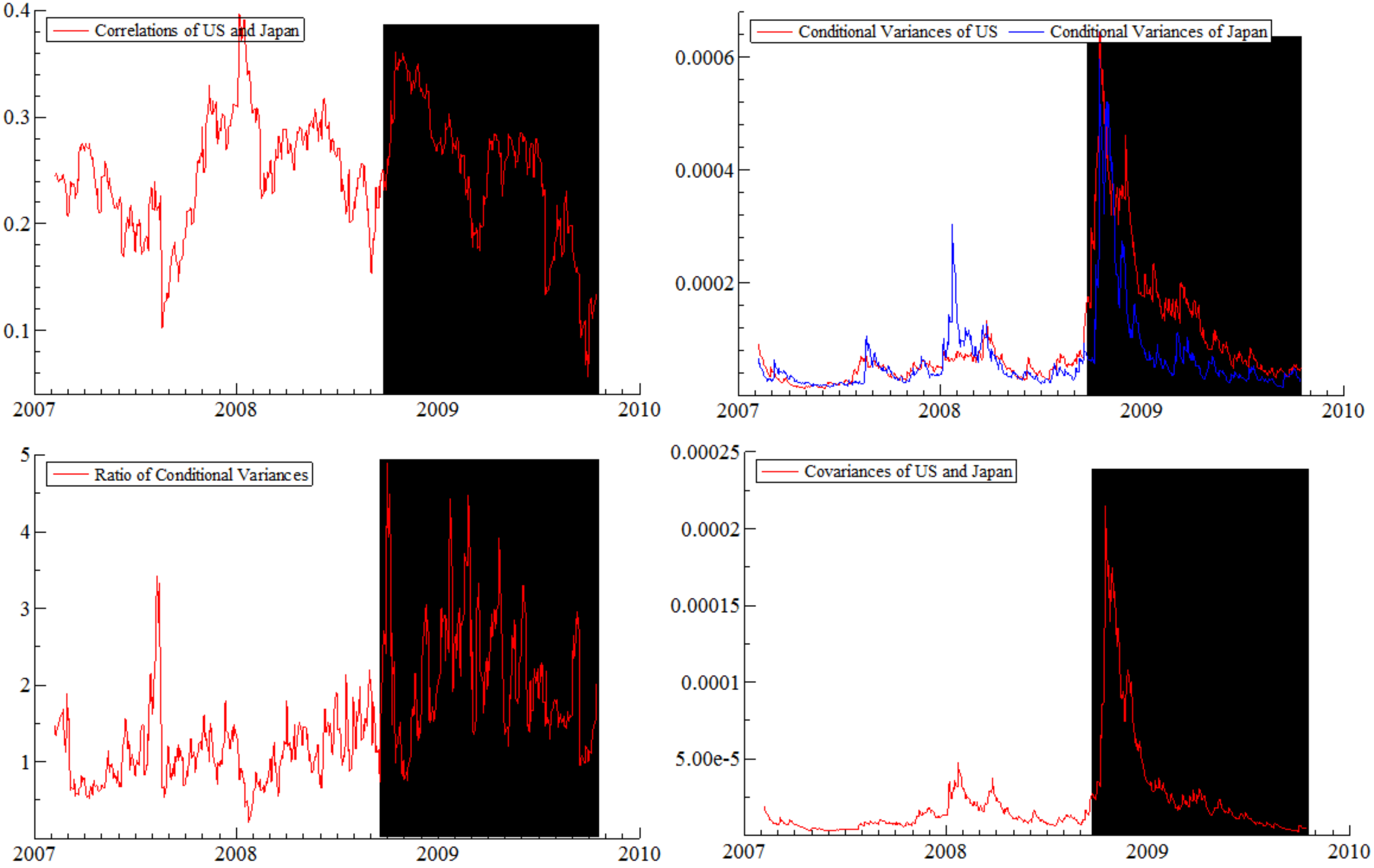


Figure A5.16: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of Spain and US

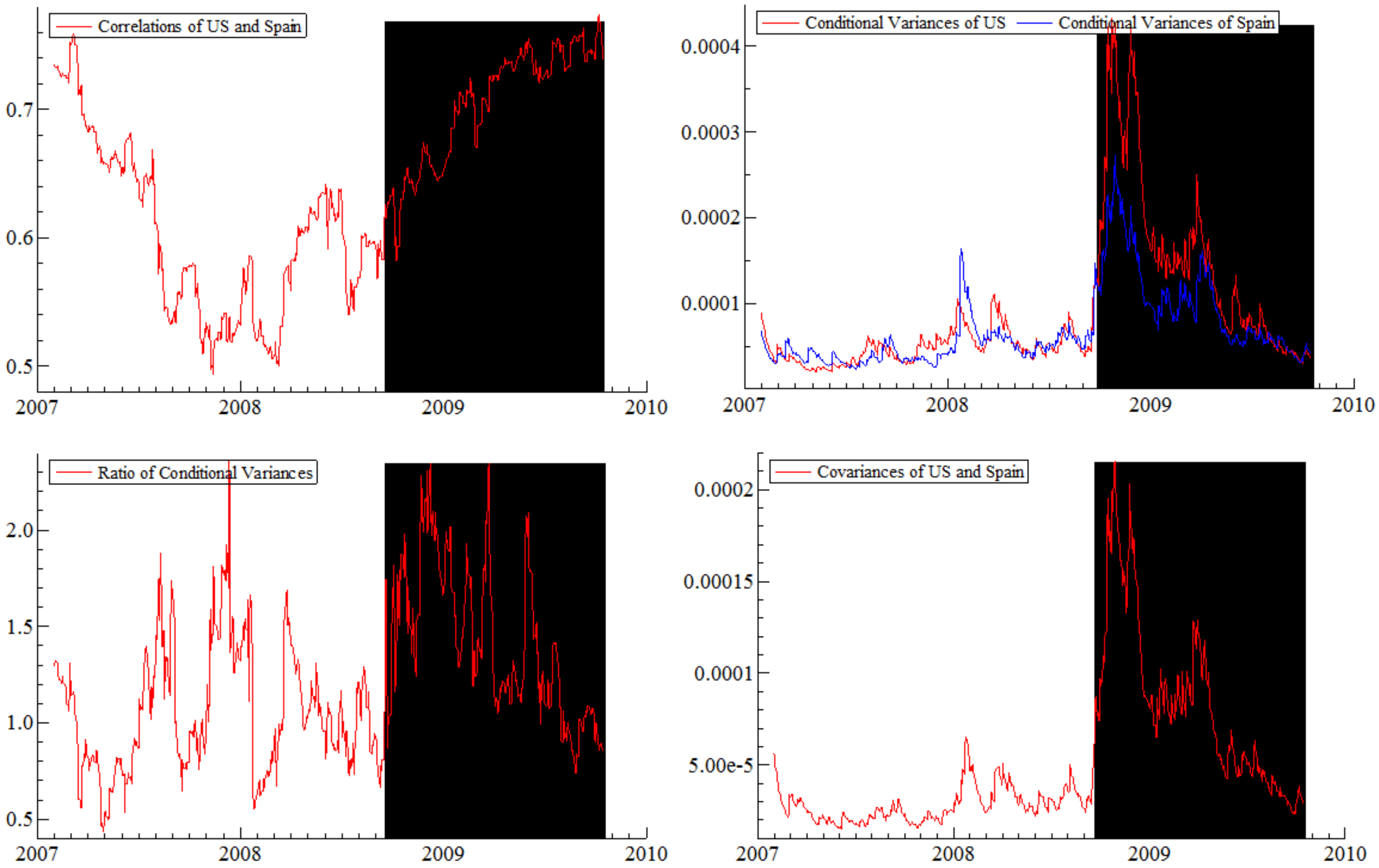


Figure A5.17: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of UK and US

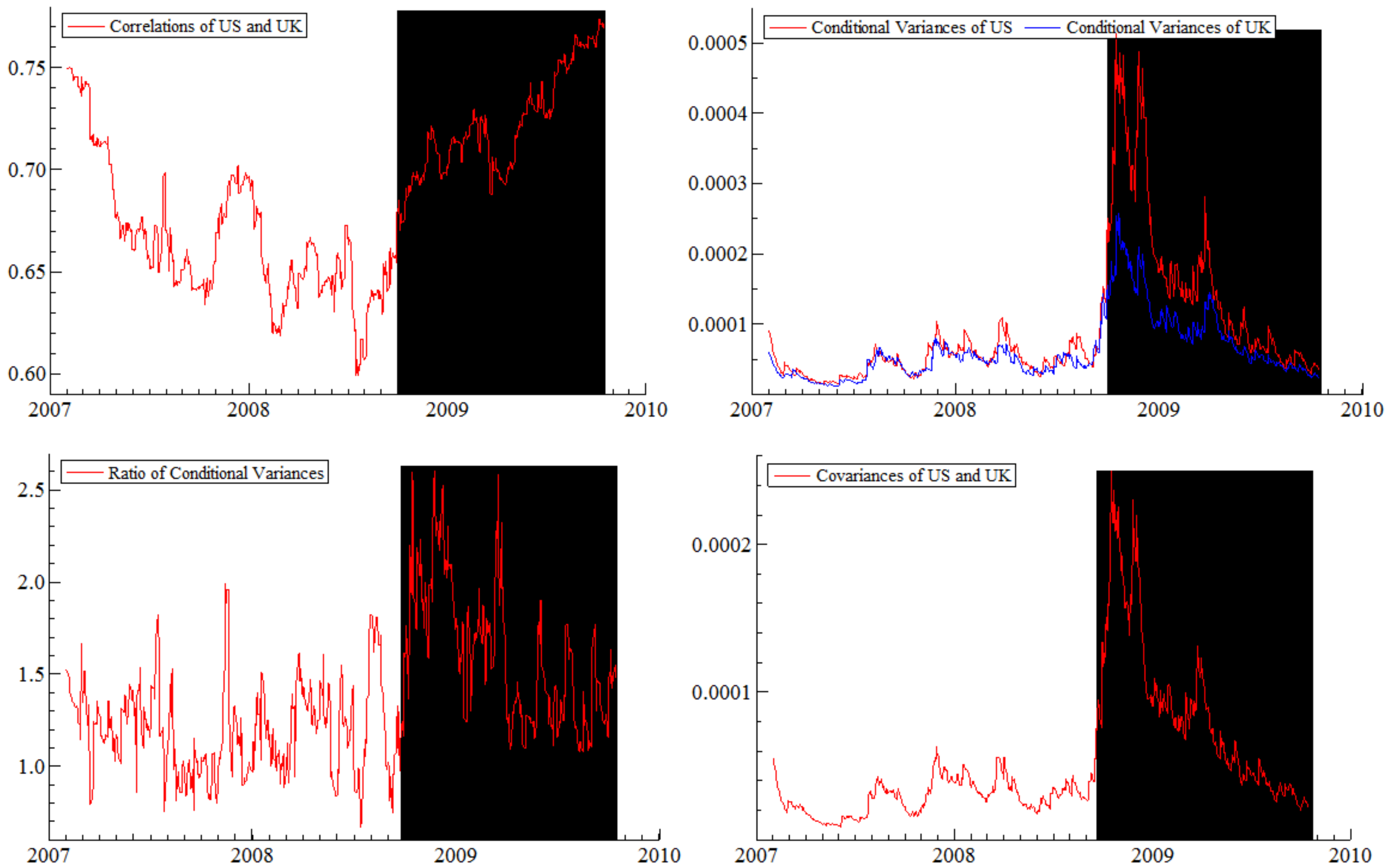


Figure A5.18: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of China and US

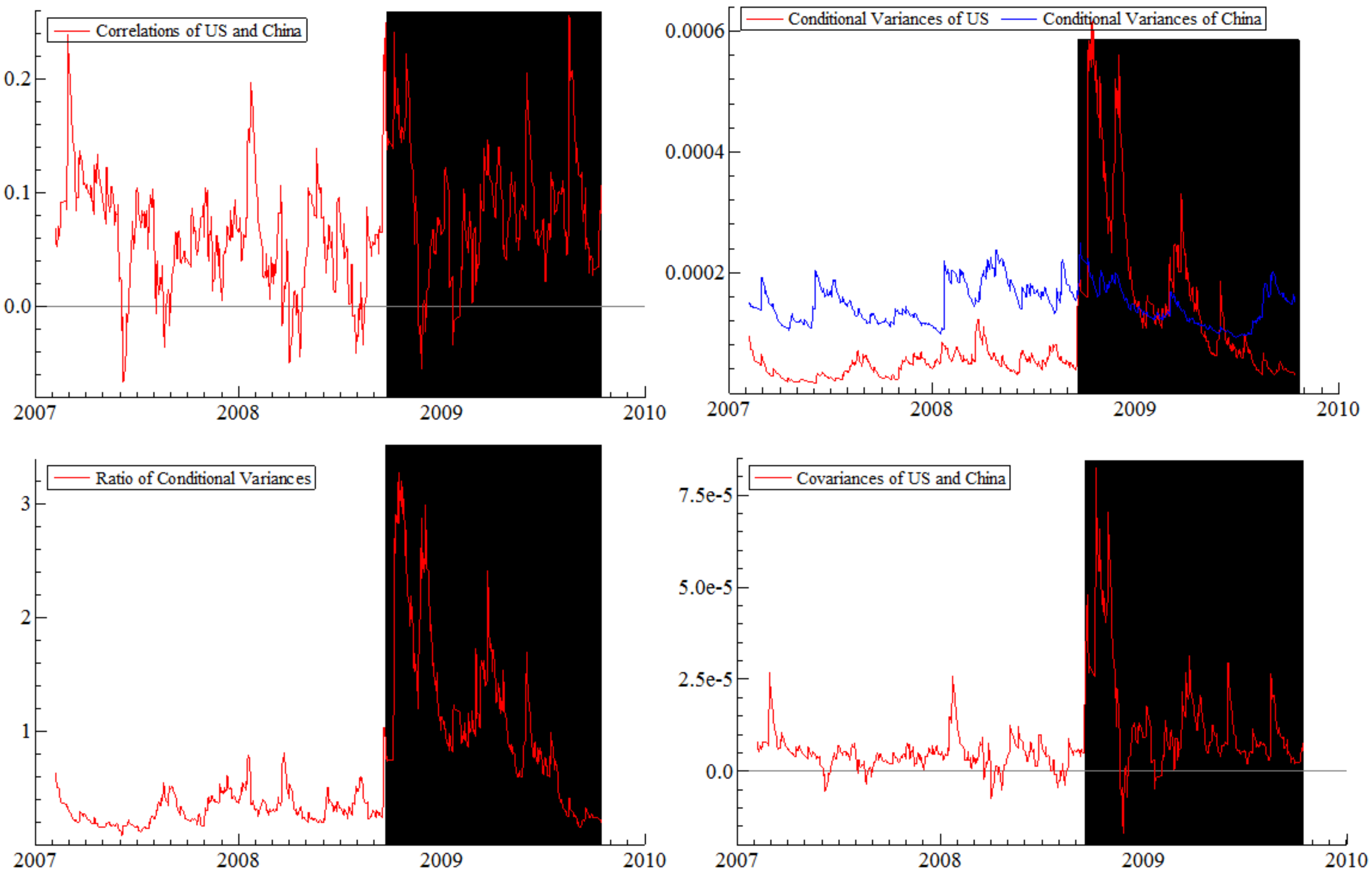
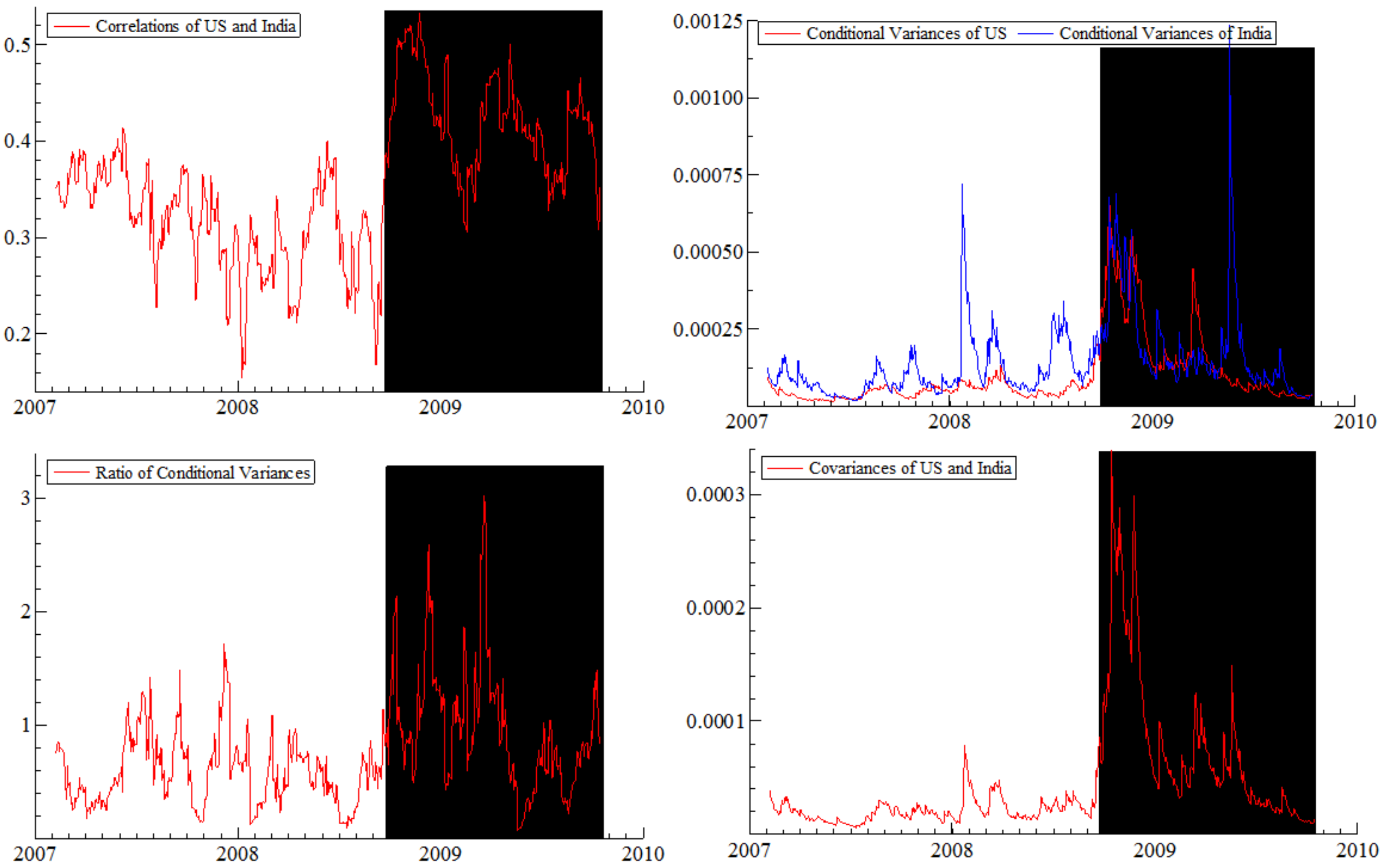


Figure A5.19: Conditional correlations, conditional variances, ratio of conditional variances and conditional covariance of India and US



6 DISCUSSION OF RESULTS

6.1 INTRODUCTION

The objectives of this chapter are threefold. The first objective is to draw some conclusion as to which is the preferred econometric methodology. In order to do this a comparison of the results obtained by using the separate VARs approach used in Chapter 4 and the dynamic conditional correlation approach (using MGARCH) used in Chapter 5 are examined in Section 6.2. This comparison, along with some theoretical considerations, is then used in Section 6.3 to identify the most preferred contagion econometric methodology in the context of this thesis.

The second objective is to use the preferred methodology identified to describe the differences found in respect to contagion in African and developed markets. This is done in Section 6.4, which summarises the differences in respect to the "long period" and "short periods" contagion events identified in the previous chapters.

The third objective is to use the findings of the thesis to examine the differences in the pathways or channels through which contagion effects develop in African markets and developed markets. In Section 6.5, I examine the applicability of the non-behavioural explanations first identified in Chapter 2, Sections 2.3.1 and 2.3.2. I then examine the results from a behavioural perspective in Section 6.6 in the context of the model framework developed in Chapter 3, Figure 3.12. This applies a number of the behavioural concepts and ideas first identified in Chapter 2, Section 2.5 to the econometric findings of this thesis. This is done as part of the process of identifying the reasons for finding differences in contagion effects in African markets and developed markets. Finally, Section 6.7 draws some conclusions in respect to the differences in the channels that contagion effects follow in respect to African and developed markets.

A preliminary observation that can be made is that it would not be unexpected to find significant differences in the channels that contagion takes in African and developed markets: this given the large differences in the pre-crisis and crisis-period correlations with the US observed in the data. This finding sits comfortably with the distinction I made between high-integration markets and low-integration markets. Within the African markets, only South Africa can be observed as possibly straddling the high-integration/low-integration dividing line.

It is necessary to point out that the behavioural interpretation made of the contagion events found in this thesis (Section 6.6) are not formally tested.

6.2 COMPARISON OF THE SEPARATE VARs AND DYNAMIC CONDITIONAL CORRELATION RESULTS

This section discusses the results obtained from the implementation of the separate VARs (SV) and dynamic conditional correlation (DCC) models applied in Chapters 4 and 5. Recall that at the end of Chapter 4, the SV model was chosen as the preferred model of the static correlation models employed (see Chapter 4, Section 4.5). Therefore, only the SV model results will be compared in this section against the respective DCC model results. It can be recalled that the findings of Chapters 4 and 5 were discussed in terms of the one long and four short sub-crisis periods. In respect to the SV methodology, only the cumulative impact of sub-period 1-4 and the long crisis period could be used in contagion testing because of the relatively small crisis windows in sub-periods 1, 1-2 and 1-3 timeframes. The respective correlation and contagion results from the cumulative impact of sub-period 1-4 and the long crisis period presented in Chapters 4 and 5, respectively, are reproduced in Table 6.1[32] below. The two approaches show clear differences in respect to contagion. It can be noted that:

- The DCC model found contagion in Botswana, Côte d'Ivoire and Mauritius in the two sample periods while the SV model did not.
- Evidence of contagion is only found from the cumulative impact of sub-period 1-4 in Morocco and Japan across both methodologies but not in the long period.
- France provided contagion in the long period across both models but not in sub-period 1-4.
- The DCC model finds more evidence of contagion in African markets (seven markets from sub-period 1-4 and five markets in the long period) than does the SV model (three in African markets from the cumulative impact of sub-period 1-4 and two in the long crisis period).
- For the developed markets, the DCC model found evidence of four contagion events in sub-period 1-4 and evidence of six contagion events in the long crisis period, while the SV model provided evidence of more contagion in sub-period 1- 4 (six markets affected) and six in the long crisis period.

[32] The DCC estimates are mean values calculated over the period in question.

Table 6.1: Correlation and contagion results using the SV and DCC methodologies

	Pre-crisis		Sub-period 1-4		Long period		Sub-period 1-4		Long period	
	DCC	SV	DCC	SV	DCC	SV	DCC	SV	DCC	SV
African markets										
BWA	-0.028	-0.038	0.045	0.104	0.011	0.051	No	**Yes**	No	**Yes**
CIV	0.028	0.024	0.110	-0.094	0.036	0.039	No	**Yes**	No	**Yes**
EGY	0.155	0.100	0.284	0.645	0.194	0.297	**Yes**	**Yes**	**Yes**	**Yes**
MUS	0.043	0.035	0.043	0.288	0.043	0.096	No	**Yes**	No	**Yes**
MAR	0.011	-0.043	0.152	0.486	0.017	0.083	**Yes**	**Yes**	No	No
NAM	0.342	0.298	0.369	0.320	0.318	0.211	No	**Yes**	No	No
NGA	0.043	-0.015	0.043	-0.281	0.043	0.044	No	No	No	No
SA	0.416	0.382	0.539	0.716	0.547	0.577	**Yes**	**Yes**	**Yes**	**Yes**
TUN	0.066	0.077	0.066	0.206	0.066	0.121	No	No	No	No
ZMB	-0.016	0.007	-0.016	0.153	-0.016	-0.012	No	No	No	No
Developed markets										
CAN	0.763	0.680	0.770	0.910	0.828	0.863	**Yes**	No	**Yes**	**Yes**
FRA	0.713	0.653	0.687	0.772	0.745	0.763	No	No	**Yes**	**Yes**
GER	0.664	0.587	0.737	0.887	0.769	0.799	**Yes**	**Yes**	**Yes**	**Yes**
ITA	0.531	0.457	0.516	0.697	0.567	0.597	**Yes**	No	**Yes**	**Yes**
JPN	0.246	0.276	0.309	0.555	0.246	0.374	**Yes**	**Yes**	No	No
SPN	0.602	0.563	0.630	0.756	0.704	0.728	**Yes**	**Yes**	**Yes**	**Yes**
UK	0.665	0.630	0.681	0.789	0.720	0.756	**Yes**	**Yes**	**Yes**	**Yes**
Other markets										
CHN	0.059	-0.001	0.149	0.013	0.091	0.142	**Yes**	**Yes**	**Yes**	**Yes**
IND	0.314	0.210	0.452	0.010	0.418	0.555	**Yes**	**Yes**	**Yes**	**Yes**

Although Table 6.1 shows a substantial number of differences, there are also some consistent results. For example, three markets (Nigeria, Tunisia and Zambia) provided no contagion in all cases.

Turning now to an examination of the correlations, it can be seen that although the two methodologies produced similar values in many instances there are also some significant differences, for example, in respect to Nigeria, Tunisia, Mauritius and Zambia. While the DCC shows no change in the correlations of these countries in the crisis periods, the SV model shows appreciable changes. For instance, the DCC correlation for Nigeria is 0.043 in all periods, but the SV correlations show −0.015 during the period of stability and −0.281 and 0.044 for the cumulative impact of sub-period 1-4 and the long crisis period. Similarly, for Tunisia, Mauritius and Zambia, which showed no change in the DCC across the two periods, show appreciable change from the cumulative impact of sub-period 1-4 and the long crisis period of the SV model. The lack of variation in the DCC coefficients in respect to some countries results from a lack of statistical significance in the alpha term in Equation 5.6 (see Chapter 5 and also Appendix 5.2).

6.3 IDENTIFYING THE PREFERRED ECONOMETRIC METHODOLOGY

Identifying the preferred methodology in respect to measuring contagion is potentially problematical. Table 6.2 shows that the results of the two methods show significant differences. So how is this choice to be made? A number of issues can be identified.

1. The SV approach is based on a single correlation estimate. Unlike the DCC approach, it does not allow for the exploration of the impact of the crisis on a time-varying basis (see Figures A5.1 to A5.19 in Chapter 5 appendix in respect to examples of time-varying correlations).
2. The SV approach can only be applied if the crisis period lasts over a sufficiently long period to provide adequate data. This can be seen to be a disadvantage in respect to this thesis as the first three short sub-periods cannot be modelled.
3. As identified in Section 6.2 above, in instances where the alpha coefficient in Equation 5.6 is not statistically significant, the lack of time variation in correlations estimated by the DCC model has to be treated with caution.
4. The functional form of volatility can potentially change significantly during a crisis period. The DCC approach has an advantage here in that volatility that takes different functional forms can be modelled. A number of these different forms have been identified in Chapter 5, Section 5.5.3 (for example, GJRGARCH model; Glosten, Jagannathan and Runkle 1993, threshold GARCH

model; Zakoian 1994, nonlinear ARCH model; Higgins and Bera 1992, nonlinear asymmetric GARCH model; Engle and Ng 1993.

5. It can also be noted that, although it has not been applied in this thesis, asymmetric correlations models are now available in respect to the DCC-type methodology (see, for example, Asai 2013).

On balance, I conclude that although the DCC methodology has some limitations in respect to my thesis (principally, in respect to modelling correlation dynamics in respect to a number of African countries) it has a number of both practical and theoretical advantages over the SV method. On this basis I use the DCC results in my examination of contagion in the subsequent section of this chapter.

6.4 CONTAGION DIFFERENCES BETWEEN AFRICAN AND DEVELOPED MARKETS

6.4.1 Differences in integration

The key differences between African and developed markets can be identified in terms of the level of *integration* of the markets with the US. Broadly speaking, African markets have relatively low levels of integration (Boamah 2014, Agyei-Ampomah 2011 and, Bekaert et al. 2011) and developed markets have high levels of integration with the US (Bekaert et al. 2011). The degree of integration is normally defined in terms of the correlation.

On this basis, Table 6.2 shows that, of the African countries, only South Africa can be described as being highly integrated with the US before the crisis, and this was only to a marginal degree. The comparative emerging markets used, China and India, are also seen to show low integration during the pre-crisis (or stable period). Of the developed markets, only Japan falls into the low-integration category. The classification of countries according to the integration level is shown in Figure 6.1 below.

Table 6.2: DCC correlations for all countries during all crisis periods

	Pre-crisis period	Sub-period 1	Sub-period 1-2	Sub-period 1- 3	Sub-period 1-4	Long period
African markets						
BWA	-0.028	0.012	0.014	0.020	0.045	0.011
CIV	0.028	0.103	0.113	0.119	0.11	0.036
EGY	0.155	0.243	0.255	0.263	0.284	0.194
MUS	0.043	0.043*	0.043*	0.043*	0.043*	0.043*
MAR	0.011	0.131	0.139	0.144	0.152	0.017
NAM	0.342	0.367	0.366	0.367	0.369	0.318
NGA	0.043	0.043*	0.043*	0.043*	0.043*	0.043*
SA	0.416	0.496	0.504	0.514	0.539	0.547
TUN	0.066	0.067	0.067	0.066*	0.066*	0.066*
ZMB	-0.016	-0.016*	-0.016*	-0.016*	-0.016*	-0.016*
Developed markets						
CAN	0.763	0.717	0.730	0.744	0.770	0.828
FRA	0.713	0.666	0.672	0.678	0.687	0.745
GER	0.664	0.708	0.716	0.724	0.737	0.769
ITA	0.531	0.477	0.484	0.494	0.516	0.567
JPN	0.246	0.257	0.273	0.290	0.309	0.246
SPN	0.602	0.617	0.617	0.622	0.63	0.704
UK	0.665	0.665*	0.669	0.673	0.681	0.720
Other markets						
CHN	0.059	0.176	0.175	0.170	0.149	0.091
IND	0.314	0.378	0.403	0.423	0.452	0.418

**There is small variation in crisis-period correlations beyond three decimal places when compared with the stable period.*

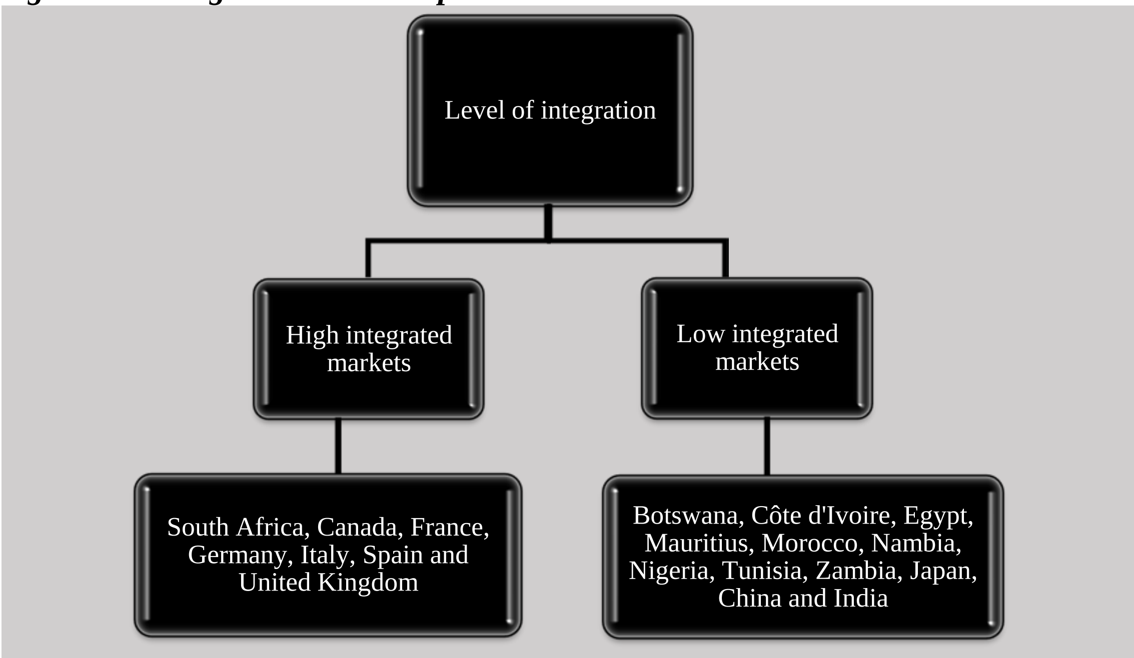
In respect to African markets, my findings (Table 6.2) are in line with those of Boamah (2014), and Agyei-Ampomah (2011). These studies report that, except for South Africa, other African markets are segmented from world markets. Morales and Andreosso-O'Callaghan (2010) also reported that the US has a strong influence on the South African market.

The low pre-crisis correlations for the next largest African markets, Egypt and Nigeria, are possibly a little surprising. It can be noted, however, that both of these markets experienced internal problems of their own before the crisis. For instance, Egypt was experiencing an internal uprising from April 2008, before the final outburst that became the Egyptian revolution in 2011. In addition, the country also experienced a food crisis between 2007 and 2008. In 2007, Nigeria was also troubled by continued turmoil in the oil-producing Niger Delta and, on the political scene; the new president elected in 2007 was faced with fraud allegations, which led to political unrest in different parts of the country. Six governors elected in 2007 were annulled in 2008 (AfDB/OECD 2008). All these problems might have had a great impact on the countries' stock markets by reducing international investment, which would in turn segment the countries from the world market, which is dominated by the US. The least-correlated African markets are Botswana and Zambia, which produced −0.028 and −0.016 during the stable period.

High correlations are evident between the US and all developed markets except Japan (0.246) during the stable period. The highest correlation is observed in Canada (0.763.) This is not surprising because Canada and the US belong to the same region and are both very advanced markets.

It can be speculated that differences in the levels of market integration may reflect a number of factors. These are likely to include the strength of trading relationships (see Figure 6.3 below) and the strength of linkages between financial markets. The latter issue became clearly apparent during the 2007-09 crisis as the spider's web of internationally traded derivative products began to unravel. This was no more apparent than in relation to Collateralised Debt Obligations (Brunnermeier 2008).

Figure 6.1: Integration based on pre-crisis DCC correlations



6.4.2 Differences in contagion

As identified in Chapter 2, *contagion* is commonly referred as occurring when correlations increase by a statistically significant amount after a shock. This is distinguished from *interdependence* in high-integration countries where the increase in correlation is not found to be significant at the 5% level (Forbes and Rigobon 2002). In low-integration countries, an insignificant increase or a decrease in correlation is identified as *no contagion*.

Using the above basis, Figure 6.2 below identifies instances of contagion and interdependence in high and low-integration countries in respect to the various test periods identified in this thesis.

For the highly integrated markets, the figure indicates that:

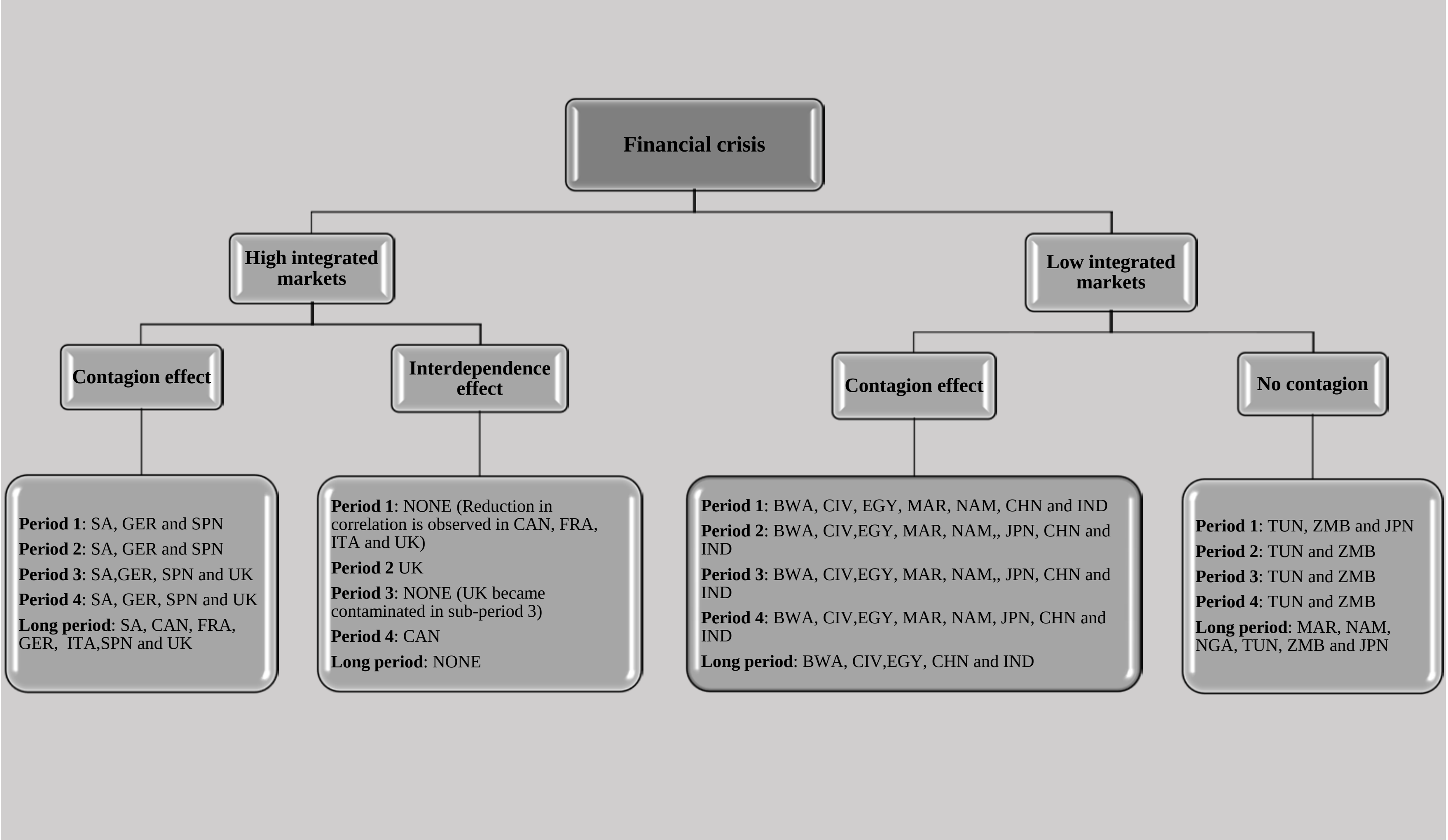
1. South Africa, Germany and Spain are the only highly integrated markets to show evidence of contagion throughout the sample periods.

2. When compared to the pre-crisis correlations, reductions in correlations are observed in Canada, France and Italy in sub-period 1 and from the cumulative impact of sub-periods 1 -2, and 1-3. France and Italy also showed reduction in correlations in respect to the cumulative impact of sub-period 1-4.
3. The UK became contaminated when contagion is tested on the impact of sub-periods 1-3, 1-4 and in the long crisis period.
4. Interdependence is found in Canada from the cumulative test on sub-period 1-4.
5. In the long crisis period all highly integrated markets appear affected by the crisis in the form of contagion effect.

For the low-integrated markets;

1. The crisis took a contagious effect in Botswana, Côte d’Ivoire, Egypt, China and India throughout the crisis periods, including the long crisis period.
2. Japan is contaminated from the cumulative impact of sub-periods 1-2; 1-3 and; 1-4.
3. Morocco and Namibia show contagion effect in the four sub-crisis periods.
4. Tunisia and Zambia show no contagion throughout the sample periods.

Figure 6.2: [33]Categorisation of market responses to different events during financial crisis



[33] Nigeria and Mauritius are omitted from the chart because of statistical issues.

African markets

The strong contagion found in South Africa, over all periods, is not surprising. South Africa is the largest market in Africa and the most integrated with the world market. Apart from South Africa, the remaining African markets demonstrated low correlation before the crisis, but interestingly a number of small markets such as Botswana, Côte d'Ivoire, Morocco and Namibia exhibited contagion during the crisis. Although my methodology (I am using the DCC results for this analysis) differs from Collins and Biekpe (2003), they also found contagion effect in small African markets (Mauritius and Namibia) prior to applying the Forbes and Rigobon (2002) heteroscedasticity adjustment.

The next largest markets in Africa after South Africa are Egypt and Nigeria. Although Nigeria is omitted from the analysis because of statistical issues, it can be seen that Egypt is contaminated in all the crisis periods.

My findings can be compared most closely to those of Asongu (2011b). Although the study adopted the Forbes and Rigobon (2002) approach, it also measured contagion across three time periods during the 2007 financial crisis (short-term turmoil period, medium-term turmoil period and long-term turmoil period). Asongu (2011b) found evidence of contagion in Botswana, Egypt, Mauritius, Namibia, Nigeria, South Africa and Tunisia in at least in one of the periods tested, even after adjusting for heteroscedasticity in accordance with Forbes and Rigobon (2002). They found only Morocco and Kenya to show no contagion in all the three periods they tested.

My findings can also be compared, from a methodological perspective, with the results of Morales and Andreosso-O'Callaghan (2010). For robustness they also adopted three testing frameworks; Forbes and Rigobon 2002, GARCH (1, 1) and GARCH errors per regional market. Using two different US indices (S&P 500 and the Dow Jones), they also found evidence of contagion in African markets. It is interesting to note that Nigeria is their only market to show no contagion in all testing frameworks and with both indices.

A further examination of the correlations in Table 6.2 provides support for the argument of Kassim (2013:80) that the nature of integration changes during a crisis and that markets often move in unison. Similarly, my results are consistent with those of Tuluca and Zwick (2001), Cheng and Glascock (2006) and Kang and Yoon (2011), who all found increased feedback and integration between markets after crisis. As can be seen from Table 6.2, except for Mauritius, Nigeria, Tunisia and Zambia, the remaining six African countries demonstrated an increase in correlations during crisis. Botswana moved from −0.028 during the stable period to 0.012 in sub-period 1 and continued to increase through to sub-period 1-4. A similar pattern is observed in Egypt and Morocco. South Africa, however, is the only African market to demonstrate continued increase in correlation throughout the four sub-crisis periods through to the long crisis period.

The table also shows that the African markets had their highest correlations during the short crisis samples. These include Botswana, Egypt, Morocco and Namibia from the cumulative impact of sub-period 1-4 and Côte d'Ivoire from the cumulative impact of sub-period 1-3. The only highly integrated African market, South Africa, had its highest correlation in the long crisis period and its lowest correlation in sub-period 1. It can also be noted that the lowest correlations for all the lowly integrated African markets were in the long crisis period. These findings provide the conclusion that *as the crisis period lengthened, the low-integrated markets stopped responding to the crisis. This* *behaviour, I argue, can possibly be explained in terms of behavioural factors (addressed in more detail in Section 6.6).*

Developed markets

With the exception of Japan, all the developed markets are classed as highly integrated with the US; therefore, it is expected that they will be subject to interdependence or contagion effects. OECD (2012:3) gave possible reasons why. They argued: “International financial integration is commonly seen as increasing economic efficiency and growth, but it may also increase countries’ vulnerability to contagion. Not surprisingly, the more banks lend to each other through cross-border loans, the higher the risk of contagion. Larger rollover risk due to shorter maturities of cross-border bank debt further increases vulnerability”.

My findings, however, suggest that contagion effects were far from uniform across the crisis periods. They show that, apart from Germany and Spain, no other developed market was contaminated in sub-period 1. A negative impact on correlation (reduction in correlation during crisis) was found in respect to; Canada, France, Italy and the UK in sub-period 1 and; Canada, France and Italy from the cumulative impact of sub period 1-2. The negative effect continued in Canada, France and Italy in sub-period 1-3. Correlation between the US and Canada increased when the cumulative impact of sub-period 1-4 is compared against the stable period in the form of interdependence. UK became contaminated sub-periods 1-3 and 1-4 after demonstrating interdependence from the cumulative impact of sub-period 1-2.

The only low-integrated developed market, which is Japan, shows evidence of contagion from the cumulative impact of periods 1-2; 1-3 and; 1-4 but not in the long crisis period. All the highly integrated markets showed evidence of contagion in the long crisis period. One possible explanation of this finding is that *as most of the other developed markets in my sample are more strongly integrated with the US than Germany and Spain, they showed no significant jump in correlation at the onset of the crisis. The high volatility observed in most of these markets during crisis (See Figures 3.9 and 3.10 in Chapter 3, Section 3.2.2.3) may merely reflect a continuation of the strong underlying integrated relationship between the markets and the US.*

My findings in respect to developed markets are similar to others found in the literature. For instance, Horta, Mendes and Vieira (2008) found significant evidence of contagion in Canada, Japan, Italy, France and the UK but not in Germany and Portugal (the authors suggest interdependence for Germany and Portugal). They also reported that Canada has the highest intensity of contagion observed. More recently, Chenguel (2014) also, examining the subprime crisis, detected that the US is a source of contagion to France, Germany and the UK.

My work also suggests evidence of contagion in other emerging markets; specifically China and India. This supports the findings of Morales and Andreosso-O'Callaghan (2010) who also found evidence of contagion in India during the 2007 financial crisis. It can be noted however that Asongu (2011b) found no evidence of contagion in India although China provided evidence of contagion for its short-term turmoil period.

6.4.3 Differences between African and developed markets

Considerable differences between these two groups can be noted from Table 6.2. It can be seen that correlations in some developed markets (Canada, France, and Italy) *fell* after the onset of crisis in sub-period 1 and did not change appreciably in respect to the UK.

There were also considerable differences within developed markets as the crisis developed. For example, while Germany continue to show an increase in correlation throughout the sample periods, Spain showed no appreciable change between sub-periods 1 and 1-2, but increased from cumulative impact of sub-period 1-3 through to the long crisis period. The only low-integrated developed market, which is Japan, showed continuous increases in correlation from sub-periods 1, 1-2, 1-3 and 1-4 demonstrating similarities with some African markets. Also observed from the table is that only the correlations from the cumulative impact of sub-period 1-4 and the long crisis period are higher than the stable period correlation in Canada. In France and Italy, only the long crisis period correlations of 0.745 and 0.567 are higher than their stable period correlations of 0.713 and 0.531, respectively.

China and India showed increases in correlation at the onset of crisis. For instance, China's correlation with the US moved from 0.059 before the crisis to 0.176 in sub-period 1. Although the correlations reduced as the crisis period lengthened, they still stood above the stable period correlation, providing the basis for evidence of contagion throughout the sample periods.

The most striking difference between the African market and the developed markets correlations is that the African markets, excluding South Africa, produced their highest correlations in at least in one, of the short sub-crisis periods. This can be contrasted with the highly integrated markets which exhibited their highest correlations in the long crisis period (as did South Africa). This finding is very interesting as it provides evidence of strong differences in the financial linkages/integration between markets-types.

6.5 NON-BEHAVIOURAL EXPLANATIONS FOR DIFFERENCES IN THE CONTAGION EFFECTS FOUND

I would argue that my results, as examined in Section 6.4, provide clear evidence that contagion effects resulting from the 2007-09 financial crisis differed considerably between African and developed markets. In this section and also Section 6.6 I examine why this may have been the case. In doing this I will examine the possible channels that contagion developed along and also, in Section 6.6, possible differences in the ways in which behavioural forces influenced these markets.

6.5.1 Type of banking system in Africa

One of the potential reasons for the differences found could lie in the differences between the banking systems of African and developed-country markets. Unlike developed market banking sectors, with their strong focus on investment banking, African banking sectors (with the possible exception of South Africa) focus almost exclusively on the retail sector. Kasekende et al. (2009:65) reported that, “most banks in Africa are engaged in the retail banking business; they deal with the general public (households) and businesses by taking in deposits and giving out loans. These banks require standard inputs such as deposits, workers (labour) and capital equipment (such as computers) in order to produce standard banking products such as consumer loans, mortgages, and overdrafts”. Similarly, Allen, Otchere and Senbet (2011) reported that the banking systems in Africa consist mainly of central banks and deposit-taking institutions made up of local banks and branches or subsidiaries of foreign banks. African banks largely avoid complex derivatives and are less dependent on external financing (A*f*DB, 2009). EIB (2013:17) also states in respect to Sub-Saharan African Banks: "Most banking systems in Sub-Saharan Africa are small in absolute and relative size. They are characterised by low loan-deposit ratios and, as a corollary, large shares of assets held in the form of government securities and liquid assets. Lending is mainly short-term in nature, with about 60% of loans having a maturity of less than one year".

Unlike their African counterparts, developed-country banks have large investment arms. They offer an array of products including currency, commodities and their derivatives. The trading of such products tends to be internationally based with large investment banks having significant presences in all of the world's major financial centres, such as London, New York, Singapore and Hong Kong. With such strong linkages between markets, high correlations between markets are not unexpected.

Beltratti and Stulz (2012) examined bank performance during the 2007 financial crisis and found the best-performing banks were those operating in a traditional banking system. While their research incorporated only one African country (South Africa), the characteristics of the better-performing banks as reported are strongly associated with Africa's banking system. They also noted that better-performing banks in developed countries, notably HSBC, rely mostly on deposit rather than investment banking.

EIB (2013) reported that Sub-Saharan African banking systems were well positioned to handle the global financial crisis in 2008. However, EIB (2013:20) also noted: "Systemic financial stress was recorded only in Nigeria, where the flight of foreign portfolio capital contributed to the collapse of a stock market bubble that had been fuelled, in good part, by margin lending by banks to equity investors. The Central Bank of Nigeria eventually took control of ten banks, collectively accounting for one-third of banking system assets, which had suffered large losses on their loan portfolios. Some major international banks with a significant African footprint experienced stresses during the crisis period, but the spill-over impact on their (largely self-funded) African operations was very modest".

It is possible to argue that the findings in this thesis of strong long-period contagion effects in developed markets may possibly reflect this underperformance of major developed-country investment banks during this relatively long crisis period. The few long-period contagion effects found in Africa may conversely, reflect the fact that the retail-based African banks did not suffer losses to the same extent as their investment bank-related, developed-country counterparts. It may well be that the short-period contagion effects in Africa are therefore more indicative of short-lived behavioural factors such as herding.

6.5.2 Presence of foreign banks in Africa

It should be noted that there are some major intraregional differences within the African banking sector. This may possibly explain why in some notable cases, for example, Botswana, long-run contagion was found. Botswana is fairly unique in that it has a relatively large foreign bank sector (see Botswana Financial Sector Review 2009/2010).

The emergence of Africa as a focal point for new investment by foreign banks over the last few years has highlighted its relative attractiveness to investors in comparison with mature economies. It is a continent with some of the world's fastest-growing economies, such as Nigeria, and offers new opportunities as opposed to the stagnation seen in many developed economies. According to the Ernst and Young (2014) Africa

Attractiveness Survey, intra-African investment and expansion is growing, with foreign direct investment (FDI) into Sub-Saharan Africa at the highest level than it has been in years; with this has come a rapid increase in the degree and extent of involvement of foreign banks on the continent. Andrew England (*Financial Times*, 2 January 2012) quoted John Coulter of JP Morgan Chase on investment in Africa: “The opportunity we see in Africa is really to build out our commercial banking business to deliver treasury and corporate banking services to our clients across Africa, at the same time opening up the way for investment banking opportunities. If we invest now, then we will reap the upturn in Africa, whether it is in five years, ten years or twenty years, but we recognise that we need to make that investment now”.

Pera (2013), argued this involvement in Africa has been paying off as follows:

- Foreign banks account for 15% of total profits and 19% of total pre-tax profits;
- Foreign bank profitability exceeds that of banks operating locally and African banks operating across the continent;
- Foreign banks earn a return on assets of 3.75%, well ahead of the average 3.03%.

Pera (2013) further noted that the distribution of foreign banks across nations of the continent is not uniform. Countries such as Egypt, Algeria and Francophone African states have long had a significant presence of foreign banks and that South Africa has seen several foreign banks, including Barclays, Credit Suisse and the Chinese ICBC, develop a presence in recent times. EIB (2013) reported that there are 12 registered branches of foreign banks in South Africa. Nigeria has seen some influx of a few foreign banks, notably Standard Chartered Bank (headquartered in London) and

Citibank (headquartered in New York, US), but the significance of foreign banks remains relatively low at less than 20%.

Evidence of contagion found in some of the African markets could be attributed to the presence of foreign banks in the region. OECD (2012:3) submitted: "Financial contagion through international banking occurs, e.g. when banks in a given country respond to deteriorations in their balance sheet by reducing cross-border loans, including vis-à-vis clients in countries that are not directly exposed to the initial financial shock". Most of the foreign banks in Africa have their headquarters in the UK, France and Portugal – these countries suffered huge losses during the financial crisis (A*f*DB, 2009).

The most vulnerable African countries to be affected through this means include Botswana, Cape Verde, Chad, Central African Republic, Côte d'Ivoire, Equatorial Guinea, Lesotho and Zambia (UN/AUC, 2009). Of these African countries, Botswana, Côte d'Ivoire and Zambia are investigated for financial contagion in this thesis. Contagion is evident in Botswana and Côte d'Ivoire. In addition, the thesis also found contagion in Egypt and South Africa, where the presence of foreign banks is documented by Pera (2013).

It has been reported that Africa has continued to draw in more foreign banks even after the financial crisis. For instance, Andrew England (2012) of the *Financial Times* reported that, since 2012 not only have Western banks sought to boost their positions in Africa, but Chinese industrial and commercial banks are also increasing their presence. Andrew England (2012) submit that; "The shift, bankers say, is driven by the stagnation of developed economies, coupled with the potential of a resource-rich, but underdeveloped continent with one billion people".

Africa's attractiveness as a destination for FDI is at an all-time high, and can be expected to continue increasing, as long as policies supporting good governance and growth are implemented. As such, there is a continued likelihood that the presence of foreign players in the banking sector is set to increase in order to take advantage of the massive potential Africa has to offer as economies grow and diversify. If this is achieved, then Africa is likely to be vulnerable to more contagion effect in the future as a result of increased financial integration with the world market.

6.5.3 African stock markets' illiquidity

The prevalence of contagion may, in part be linked to the size and the liquidity of stock markets. It will be argued in Section 6.6 that *social networks* may possibly be a key behavioural driver of contagion. Relatively small and illiquid markets may reflect the fact that markets contain a relatively small number of active traders. In such circumstances social networks are likely to be relatively small among the trading community, which has been shown to encourage contagion effects (Gai and Kapadia 2010).

The fact that there is relatively low capitalisation in many African markets indicates that illiquidity may be an issue in African contagion. Table 6.3 shows the market capitalisation of listed companies for all countries. Values are provided by the World Bank (2014) in US dollars. From the table, we can see that the South African market is the most liquid African market. In 2007, the JSE traded stocks worth $833,547,930,000, followed by Egypt at $139,289,000,000. Zambia and Tunisia traded stocks worth only $2,345,885,000 and $5,355,080,000 in the same year. It is also evident from the table that the 2007-09 crisis impacted upon the African markets as evidenced by the reduction in the market capitalisation of all markets in 2008.

The values for African markets are hugely different from the value of stocks traded on developed-country markets. The highest market capitalisation was observed in Japan at $4,453,474,908,957 in 2007. For the highly integrated markets, the highest market capitalisation in 2007 was in the UK at $3,858,505,426,696. This presents an area of concern for the African countries and their stock market development.

Table 6.3: Market capitalisation of listed companies in US billion dollars

African markets	2006	2007	2008	2009	2010
BWA	3.95	5.89	3.56	4.28	4.08
CIV	4.16	8.35	7.07	6.14	7.10
EGY	93.48	139.29	85.89	89.95	82.49
MUS	3.60	5.67	3.44	4.74	7.44
MAR	49.36	75.49	65.75	62.91	69.15
NAM	0.54	0.70	0.62	0.85	1.18
NGA	32.82	86.35	49.80	33.32	50.88
SA	715.03	833.55	491.28	704.82	635.35
TUN	4.45	5.36	6.37	9.12	10.68
ZMB	1.19	2.35		2.80	2.82
Developed markets					
CAN	1,700.71	2,186.55	1,002.22	1,680.96	2,160.23
FRA	2,428.57	2,771.22	1,492.33	1,972.04	1,926.49
GER	1,637.83	2,105.51	1,107.96	1,297.57	1,429.71
ITA	1,026.64	1,072.69	520.86	317.32	318.14
JPN	4,726.27	4,453.47	3,220.49	3,377.89	4,099.59
SPN	1,323.09	1,800.10	946.11	1,297.23	1,171.61
UK	3,794.31	3,858.51	1,851.95	2,796.44	3,107.04
Other markets					
CHN	2,426.33	6,226.31	2,793.61	5,007.65	4,762.84
IND	818.88	1,819.10	645.48	1,179.24	1,615.86

Source: World Bank, 2014

Further evidence of Africa's illiquidity is provided in Table 6.4. As it was difficult to obtain accurate market listings for all countries especially the African markets, we rely on domestic listed companies' data provided by the World Bank (2014). It is evident from the table that seven countries out of our total of ten African countries have less than 60 domestic listed companies on their exchanges. The smallest numbers come from Namibia, Botswana and Zambia.

These figures suggest that, apart from South Africa and Egypt, most African stock markets are relatively illiquid having minimal trading activities and a small number of listed companies. Allen, Otchere and Senbet (2011) attributed some of the problems of the Sub-Saharan African stock exchanges to the concentration of trade in a few stocks and the dominance of few firms on some stock exchanges.

The table has been removed due to third party copyright. The unabridged version of the thesis can be viewed at the Lanchester Library, Coventry University

Source: World Bank, 2014

It was also reported by Tafirenyika (2012:20 August, 2014) that: "African stock markets are still small and often dominated by a handful of large corporations. For example, the conglomerate Dangote Group makes up about 30 per cent of the Nigerian Stock Exchange. Trading in shares is less frequent, and when it happens, it is usually limited to a few firms. Many do not have access to reliable and up-to-date information technology; in some, trading is done manually. Lack of liquidity is a major weakness, and in many cases, the general public does not have confidence in the integrity of stock exchanges". In Sub-Saharan Africa, the ten largest companies accounted for 48.9% of the total value traded in aggregate stock markets in 2011, shares are rarely traded and turnover ratios are low by international standards (Masetti and Mihr 2013). However, according to Masetti and Mihr (2013), although the lack of efficiency in the markets and the challenging investment environment are still causes for concern, equity returns have been high.

Returning to the issue of contagion, I argue that there is ample evidence cited above to suggest there is an illiquidity problem. This, along with the associated social networking issue, may have had a considerable role to play in explaining contagion in Africa.

6.5.4 Trade relationships

A study by Eichengreen and Rose (1999) argued that the international trade channel is the financial transmission mechanism in advanced nations. If this is the case, it can be argued that for Canada, Japan, Germany and the UK, trade has paid a role in the contagion/interdependency between US and these financial markets. Evidence of trade values is provided in Figure 6.3 below.

The contagion found in respect to China can also be potentially attributed to trade linkages. However, as can be noted from the chart, trade linkages between the US and most African countries are relatively low (Nigeria is a special case given the oil sector).[34] Canada has the highest trade relationship with the US among all markets. This, as can be noted from Table 6.2, is associated with Canada having the highest correlation with US market.

[34] http://www.ustr.gov/countries-regions/americas/canada and http://actionplan.gc.ca/en/page/bbg-tpf/bilateral-relations-canada-us-trade-and-investment

Changes in market correlation (and, by association, contagion) may possibly be associated with changes in trading patterns. For example, Xinhua (China.org.cn: 27 March 2010) quoting Chinese vice-commerce minister Zhong Shan, reported that: "Since the outbreak of the international financial crisis, China has been supporting the efforts of the American people to tackle the crisis. On the one hand, China has increased imports from the US".[35] Similar major changes in other US-emerging market trade relationships have been reported to have occurred as a result of the 2007-09 crisis. It was reported by the Indian Consulate General[36] that, "during the year 2007, the basket of US imports to India included exceptionally large imports of aircraft/parts, which resulted in a leap in the growth rate of US exports to 54.7%. With this component excluded, the growth rates of US exports in 2007 and 2008 were 37.5% and 39.9%, respectively".

The impact of trade linkages on contagion/interdependence is likely to be difficult to establish given that any relationship will be an indirect one. Any changes in trading patterns associated with the crisis would have an impact on the share prices of exporting companies and on the market as a whole. The fact that the Chinese stock market is dominated by export-oriented manufacturing companies suggests that the argument that trade relationships can play a role in contagion has strong credibility in respect to markets such as China.

[35] http://www.piie.com/publications/wp/wp.cfm?ResearchID=162
[36] http://indianconsulate.com/page/display/92/33

37

This table has been removed due to third party copyright.

Source: U.S Census Bureau, 2014

[37] Note: All figures are in US million dollars on a nominal basis, not seasonally adjusted

6.5.5 Sector impacts

It can be noted that the 2007-09 financial crisis initially developed in the financial sectors of developed-country stock markets before it spread to other sectors and, subsequently, internationally in the form of contagion effects. This may possibly partially explain the timing of contagion events in Africa.

In Western markets such as the US and UK, large commodity-based natural resource companies such as oil and mining companies, such as RTZ and BHP-Billiton, initially rose in response to the crisis as investors saw these as safe-haven stocks given their strong links with Chinese economic growth. Given that large parts of the African markets are resource-based, especially in South Africa, it is possible that the initially slow response of African markets to the crisis may have reflected African investors *anchoring* on the natural resource sectors in the West. It is evident from the returns charts in Figures 3.6 to 3.8 (Chapter 3) that declines across all African markets started in the last quarter of 2008, which was considerably later than occurred in most developed markets.

Some recent papers, such as Morales and Andreosso-O'Callaghan (2010) (see Section 2.7.1, no. 10, Chapter 2) defined the starting point of the crisis at an earlier point than I do in this thesis. However, it can be noted that during the initial phases of the crisis the effects on developing countries were relatively modest. In particular, Africa is said to have escaped the initial crisis that engulfed world economies in 2007 and the early part of 2008. The timing of contagion events in Africa may well reflect the fact that the downturn in the natural resources sector in developed markets occurred significantly later than the initial impact on the financial sector.

Section conclusion

It is clear from this section that there are a number of plausible explanations that may, in part, be able to explain elements of the findings of this thesis. It may very well be that they all had some role to play in what was a highly complex process that impacted upon the world's financial markets in many different ways. What this section fails to consider in detail, however, is the impact of market psychological factors and behavioural factors on market movements. By 2007, communication networks had developed to such an extent that information could reach market players across the different markets of the world almost instantly. How did the series of "shocks" they faced impact upon their behaviour? This is an issue that I will consider in the next section.

6.6 A BEHAVIOURAL INTERPRETATION OF THE DIFFERENCES IN THE CONTAGION EFFECTS FOUND

In discussing the nature of the 2007-09 financial crisis in a behavioural finance context, it is useful if we can attempt to quantify what was happening to *market sentiment* throughout this period. The most useful tool in this area in respect to US markets is the VIX, which is popularly known in the market as the gauge of fear. The VIX of implied volatility was developed by Whaley (1993) to gauge market expectations of 30-day volatility. Subsequently in the literature, attempts have been made to quantify the level of market fear associated with different values. For example, D'Anne (2012:285) identified the following fear index:

“$5 - 10 = Extremely\ low\ anxiety = extreme\ complacency$

$10 - 15 = Very\ low\ anxiety = high\ complacency$

$15 - 20 = Low\ anxiety = moderate\ complacency$

$20 - 25 = Moderate\ anxiety = low\ complacency$

$25 - 30 = Moderately\ high\ anxiety$

$30 - 35 = High\ anxiety$

$35 - 40 = Very\ high\ anxiety$

$40 - 45 = Extremely\ high\ anxiety$

$45 - 50 = Near\ panic$

$50 - 55 = Moderate\ panic$

$55 - 60 = Panic$

$60 - 65 = Intense\ panic$

$65+ = Extreme\ panic$”

On this basis, the value of 21.72 on 15/10/2009, which is the date I identify as the end of the crisis, is at the lower end of the fear spectrum and the values at the end of each of the sub-periods I identify are all at the “extreme panic” end of the spectrum.

Sub-period 1 (15/09/2008-10/10/2008) VIX value = 69.59

Sub-period 2 (15/09/2008-17/10/2008) VIX value = 70.33

Sub-period 3 (15/09/2008-27/10/2008) VIX value = 80.86

Sub-period 4 (15/09/2008-20/11/2008) VIX value = 80.06

Before I use behavioural finance-associated concepts to examine my findings in the context of behavioural decision biases, it is important to understand that the behavioural finance associated concepts adopted in this section are not statistically tested and should therefore be regarded as hypotheses.

In dealing with the behavioural concepts used in this section, it is useful to introduce some of the related concepts and ideas introduced earlier into the literature by market analysts who were originally known as chartists, but are now more commonly known as technical analysts.

Dow theorists (see, for example, Kirkpatrick and Dahlquist 2010) focused on identifying turning points in markets and one of the key concepts in respect to the bottom of a bear market phase is the notion of *market capitulation.* Dow theorists see markets driven by the forces of “fear and greed” and this is seen as introducing cyclical-based oscillations within the upward bull market trend or, as we see in the case of the 2007-09 financial crisis, cyclical oscillations around the downward bear market trend. An initial market fall will initially be arrested when “bargain hunters” enter the market believing that the market fall has been overdone. This is the “greed” that drives the market and will see the market recovering from its lows. The top of this short-run cycle is reached when “profit-takers” enter the market and sell. This is the “fear” driver asserting its dominance over market activity and reflects the fear of losing profits (or, alternatively, incurring further losses).

The Dow-theory-based technical analyst will attempt to identify the point of *capitulation*, which is a final emphatic sell-off that represents the bottom of the bear market. This is often seen as occurring where investors are fearful of a systemic collapse and, as a consequence, develop a panic-driven “sell at any price” attitude that reflects a fear of losing everything. We can possibly see this notion of capitulation within the context of behavioural finance theory.

Kahneman and Tversky’s (1979) prospect theory suggests that investors show aversion to realising losses. Specifically, there is a tendency to keep assets whose prices decreased since they were purchased in the portfolio as they are averse to realising losses. Shefrin and Statman (1985) called this the *disposition effect*. This would explain part of the 2007-09 crisis. When the market first began to fall in 2007 this effect meant this process was initially slow. There is the tendency to keep assets as they hope the sell-off was a market correction and the bull-run will resume. Szyszka (2010) argued that during the financial crisis, the disposition effect gave way to a panic-driven sell-out. I argue that when there are large falls initiated by significant shock events, such as Lehman, investors may panic and we can have *capitulation* in markets. Investors cannot see the bottom of the market and fear a systemic breakdown.

What was extraordinary about the 2007-09 crisis is that there were a series of sub-period shocks where the VIX spiked above the extreme panic level of 65+. Therefore they *all* had the potential to be seen by the market as capitulation-style events from a US perspective. From a contagion perspective, it might be expected that shocks in the US may initially have had a limited impact on integrated markets due to loss aversion and associated disposition effects, leading to no large sell-off. Worldwide contagion is more likely to occur if an event was large and perceived as having global implications. In effect, if the shock is seen as a capitulation-type event, that leads to a fear of the global financial system risking systemic failure.

However, the correlation analysis in Table 6.2 would appear to indicate that the impact of the shock was not uniform worldwide; it was clearly different in respect to Africa and developed markets. For example, whereas in African markets the first sub-period shock led to a general increase in correlation, in developed markets the picture was more mixed with three countries (Canada, France and Italy) showing considerable falls.

Figure 6.2, conversely, shows that in the long period there is strong evidence of contagion in developed markets but only limited evidence in African markets.

In the remainder of this section I examine possible behavioural explanations for these differences. I would argue that the differences identified below are also a reflection of the differences in the extent of integration of African markets and developed markets, as identified in Section 6.4.1 above.

6.6.1 Behavioural factors leading to market contagion

As mentioned in the introductory section of this chapter, none of the behavioural concepts in this section is formally tested. I however find herding to be intuitively appealing in explaining the process of contagion found in both developed and African markets because;

- In much of the financial contagion literature, contagion is described as reflecting herding behaviour (Kaminsky, Reinhart and Vegh 2003, Edwards 2000, Claessens and Forbes 2004, Dornbusch and Claessens 2000) even in the presence of different economic fundamentals.
- Analyses of correlations show that African markets are not strongly correlated with the US before the crisis. My findings show pronounced increase in correlation in the African markets during the crisis which resulted in evidence of contagion being found. I argue that this indicates a change in the traditional relationship between African markets and the US that is consistent with herding behaviour. I found some support to this approach in Thanyalakpark and Filson (2001) who investigated contagion as herding resulting from an increase in

correlation after crisis. Their motivation is also based on the fact that herding is widely accepted and documented as cause of contagion.

- It is also observed from literature review that financial contagion is sometimes defined in terms of herding behaviour. For instance one of the definitions of contagion given by the World Bank is that; "Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behaviour".[38]

Although Section 2.5.1.2 has distinguished between *intentional* and *unintentional* herding behaviour the thesis has recognised the difficulty in identifying which of these categorisation is possibly more associated with the crisis under study, particularly in African markets. Two reasons are related with this difficulty: (i) anecdotal evidence suggests that limited information on market activities in Africa creates room for few decision formers and by association, intentional herding (sentiment driven) could occur and; (ii) the fact that the crisis under study is the most popular in recent history and probably the worst since the 1930's would suggest that market participants reacted to fundamental information from the US market and by association, unintentional herding (fundamental driven) could occur. For these reasons, in this section, *I argue that differences in which the crisis impacted upon the African and developed markets are better explained in terms of differences in the speed with which the herding process developed*.

It can be noted that Hwang and Salmon (2007) argued that in developed markets the herding process can be relatively slow to develop (they were looking in the context of

[38] The permanent World Bank URL for contagion definition is http://go.worldbank.org/JIBDRK3YC0.

stock market bubbles, which, they argue, can take a number of years to develop). I argue in this thesis that the differences found between African and developed markets means that herding process is likely to develop more rapidly in Africa. I argue that this difference can partially explain the differences in respect to correlation changes and contagion identified in this thesis.

In Chapter 2 (Section 2.5), I identified the types of behavioural biases and other behavioural factors that can affect investor behaviour. I will now examine differences in the ways in which these may affect African and developed markets. These will focus on the following socionomics:

- Information effects
- Social networking effect
- Social mood effects

In Lintner's (1998) opinion, behavioural finance is "the study of how humans interpret and act on information to make informed investment decisions". The speed with which information is generated and acted upon can to some extent depend on the size and extent of the social networks that generate *secondary* information.

Primary information from US financial markets (such as stock prices and volumes data) is disseminated almost instantly around the world. However, before this information is acted upon it has to be interpreted and this secondary information will often depend on the advice or influence of friends, colleagues and social influences (Hede 2012). The degree of social influence itself is affected by status and expertise. With growing social and professional networks such as LinkedIn, Twitter and ResearchGate, social influence effects increase. Therefore, it is possible that low quality information, such as rumours or noise, is repeated more frequently through the social network than high quality information. As the low quality information gets repeated by multiple sources, it achieves credibility overtime (DeMarzo, Vayanos and Zwiebel 2003). Investors who do not have access to inside information on financial markets can act irrationally, using the low quality information that leads to *noise trading* (Thaler 1993).

Social effects can also have significant influence on individual judgement as pressures to conform can be high. According to Scherer and Cho (2003), people with stronger social linkages had more similar perceptions of risk. The manners in which individuals perceive risks also become similar with increasing group interaction. Olsen (2004) suggested a particular form of social network structure in investment markets that significantly affects the speed with which information and influence pass through society. The structure, according to Olsen (2004), involves few perceived experts and a large number of investors who trust specific experts. This is termed the "aristocratic network", characterised by the rapid spread of influence and the emergence of trends. However, the loss of some key experts causes the rapid collapse of the network, leaving large numbers of investors isolated from sources of trusted expertise. The consequence of this loss is the discrediting of the system; this results in instability and lack of direction. This type of social network exhibits a power law distribution that involves fat-tail (high kurtosis) outcome distributions. Analysis of stock market returns in financial literature suggests that they tend to follow fat-tailed distributions (see Haas and Pigorsch 2007; Kittiakarasakun, and Tse (2011); Aparicio and Estrada 1997) consistent with power laws and aristocratic social networks. These are especially prevalent during financial crises where daily prices swings of 4 and 5 standard deviation units are frequently observed.

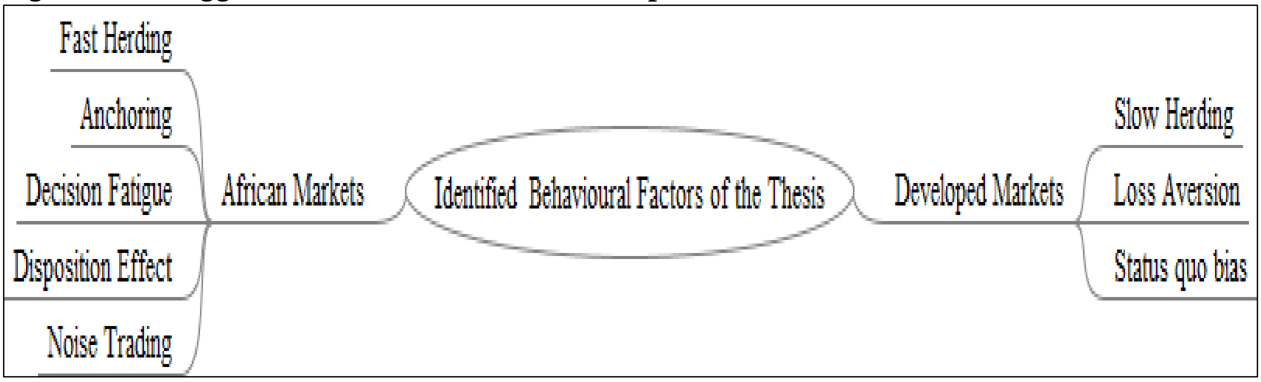
Strongly related to the impact of social effects are social mood effects (Forgas 1995, Redhead 2008 and Nofsinger 2005). These are generated through the interactions occurring within social networks and reflect the shared experiences of members of the network.

The question arises as to why these combined *socionomic* factors would lead to this secondary data and acted upon more quickly in Africa than in developed markets. The answer possibly lies in the small, illiquid nature of African markets (with the exception of South Africa). Section 6.5.3 identifies that in comparison to developed markets, African exchanges generally have few listed companies and relatively low levels of capitalisation. This will also be reflected in the relatively low numbers of active traders in African markets and therefore, by implication, relatively small social networks of stock market traders.

This can be contrasted with the vast, and liquid, nature of developed markets with large numbers of both active professional and non-professional traders. The social networks in these markets are, by implication, going to be much larger than those found in African markets. Whereas in African markets there may be a few dominant opinion-formers in the social network, in developed-market social networks there are likely to be a number of competing high profile opinion-formers. This suggests that the generation of consensus in African market social networks is likely to be substantially quicker than the generation of consensus in their developed-market counterparts. The implication of this for herding behaviour is likely to be highly significant. Specifically, it suggests that herding is likely to occur at a faster speed in Africa than in developed markets as secondary-information-based consensus is likely to develop at a faster rate in these markets.

Although *fast herding* appears to be the principle behavioural difference between African and developed markets, there are other differences that can be observed as well. These differences are identified in Figure 6.4 below and are discussed in the following two sub-sections. I have developed this framework through an examination of the results from my econometric analysis from a behavioural finance point of view.[39]

Figure 6.4: Suggested behavioural biases in sampled markets



Before I discussed behavioural concepts further, it is useful to note that contagion effect found in African markets could be due to portfolio diversification. For instance, Goldstein and Pauzner (2004:152) present a model of financial contagion whereby crisis occurs because investment portfolios are diversified across countries which leads to the transfer of negative shocks from one part of the world to another. Their findings support the hypothesis of contagion events due to diversification and reported that the "occurrence of a crisis in one country increases the probability of a crisis in the other (Goldstein and Pauzner 2004:175)". Boyer, Kumagai and Yuan (2006) separated emerging market stocks into accessible (eligible for purchase by foreigners) and inaccessible (not eligible for purchase by foreigners) categories to examine the degree to which the categorised stocks co-move with the crisis country index return during the

[39] It can be noted that this differs from the common approach taken in much of the behavioural finance literature. Studies of behavioural biases commonly employ the application of primary data such as questionnaires to test evidence of biases among private or institutional investors in specific countries, markets or sectors (Suto, Menkhoff and Beckmann 2005, Constantinos 2010, Aduda, Oduor and Onwonga 2012, Lowies, Hall and Cloete 2013, Shiller, Konya and Tsutsui 1988).

1997 Asian crisis. Using Thailand as the crisis country and a range of emerging and developed countries, the authors found that increase in correlation during the crisis period was particularly prevalent for accessible returns. Kodres and Pritsker (2002) developed a multiple rational expectations model of asset prices to assess financial contagion through various channels with emphasis on cross-market rebalancing. They found that contagion occurs through cross-market rebalancing where market participants in one country are hit by idiosyncratic shock and transfers the shock abroad by optimally rebalancing their portfolio's exposures to macro-economic risks through other countries' markets. The authors submit that cross-market rebalancing could explain contagion between Asia and Latin America during the crises of the 1990's even though the macro-economies of the two regions are weakly linked. For the markets under study (African markets and the US) evidence of low correlation identified in Section 6.4.1, might suggest weak linkages between most African markets and the US. For this reason, I suggest the hypothesis that the contagion events found in African markets could be a reflection of foreign investors rebalancing their portfolios in African markets. This type of behaviour commonly referred to as portfolio rebalancing in portfolio diversification literature has been identified by researchers such as Kaminsky and Reinhart (2000) as a cause of financial contagion. Moser (2003:161) reported that: "Several authors have pointed out that international investors could undertake such portfolio rebalancing in response to a crisis in one country, and thereby put other emerging economies in trouble by selling their assets or calling loans".

Before continuing onto socionomics identified at the beginning of this section, it is important to note that examining the hypothesis that foreign investors withdrew their investment in African markets or ascertaining the number of foreign investors within each African market is beyond the scope of this thesis but, might present a credible future research area.

6.6.2 Behavioural biases in African markets

1. ***Fast herding***

In terms of the movement of correlations during all crisis periods, I identify that the Africa markets reacted more quickly than their developed counterparts during crisis. Results show that all African markets had low correlation with the US before the onset of the crisis (Table 6.2). These values increased immediately after Lehman's crisis. This behaviour, in essence, supports the hypothesis of fast herding behaviour that leads to the short-term contagion effect found in African markets and other low-integrated markets.

Fast networking effects reflect the relatively few investors trading in markets, leading to the fast spread of secondary information and emotions. The findings of this thesis are supported by the argument of Prechter (1985, 1999) that increases in correlation as markets fall are consistent with herding behaviour when investors are faced with a relatively uniform set of stimuli. Although African markets were not faced with a subprime problem as in the US, the dominant position that the US holds in the world means that the crisis of such a nation can easily be transmitted through herding. In effect, the US became the stimulus that all African countries had in common. Prechter's (1985, 1999) arguments fit well with my findings in Table 6.2 that all African markets correlations (excluding markets with insignificant alpha in their DCC equations) increased in sub-period 1 and continue to increase in subsequent sub-periods. A further reason for the fast herding behaviour observed in the African markets could be the observation that developed-country investors withdrew money from emerging markets.

This kind of investor behaviour is commonly associated with contagion effect arising from informational asymmetries (Scardovo, Gatti and Ventola 2010 and Račickas and Vasiliauskaitė 2011).

The relative importance of institutional investors can potentially have an impact on the speed of herding. Anecdotal evidence suggests that in African markets institutional investors make up a large proportion of the investor population. For example the experiences of the current author in respect to Nigeria are that institutional investors (brokers and professional fund managers) dominate the markets because of relatively low levels of investment knowledge in the general Nigerian population.

The current author would argue that having relatively large numbers of institutional investors is likely to speed up the process of herding. This is because investment networking effects are likely to be stronger and investment networks are likely to be more *aristocratic* in nature. Allied to the social networking issue, herding speed may increase due to reduced levels of conservatisms and increase in the impact of noise trading.

It can be noted that although institutional investors are important in developed markets (for example fund managers) there are still large numbers of private and non-professional investors who have relatively strong levels of investment knowledge. In the current author's opinion, this means that institutional investors may be relatively more important in African markets than developed markets. This is one of the reasons why I believe herding effects may occur at a faster pace in Africa than in developed markets.

2. *Anchoring*

A further feature of the 2007-09 crisis that may have strengthened the tendency for markets to herd was the tendency for investors to *anchor* on US market performance as extreme events that they felt they did not fully understand unfolded. Ricciardi and Simon (2001) suggest anchoring results in investors using a common reference point. This logic could have been applied by African investors during the 2007-09 financial crisis. For instance, the cost of information, especially in relatively small and illiquid markets (for example, Cote d'Ivoire and Botswana), would have left investors with no choice but to anchor on events happening in the US. Another possible reason for suggesting anchoring on the US by African markets could be caused by issues relating to the speed of arrival of information into these markets. As evident in Table 6.2, correlations in Botswana, Egypt, Morocco and even South Africa kept increasing from their previous correlation value in all four sub-periods.

3. *Decision fatigue*

As can be noted from the VIX in Figure 3.5 (Chapter 3), the distinguishing characteristic of the 2007-09 financial crisis is its long nature characterised by a series of sub-shocks. From a behavioural finance point of view, I asked how the attitude of investors changed as subsequent phases of the crises unfolded. Did they become *habituated* to crisis in the US and stop responding? My question is answered by examining how correlations changed in response to the low-integrated (mainly African) markets in this work. I contend that this shows evidence of *decision fatigue* in these countries. For instance, the correlations in Botswana, Côte d'Ivoire, Egypt and Morocco show increasing levels from the stable period through to cumulative impact of sub-period 1-4, indicating that investors in these markets initially reacted in a standard way to each high volatility period tested. However, it can also be noted that the correlations from this group of markets dropped in the long period, suggesting behaviour changed. This, I speculate, was due to decision fatigue. Mood could have played a role in this regard. As the markets are small and moods are shared more quickly as a result of social network effects, the perpetual losses in the markets will be discussed repeatedly; eventually investors would stop responding to the crisis in the long run as they could not find a safe haven. Instead, the frequent decision changes required in response to the crisis eventually induced decision fatigue and the decision not to respond to events in the US. This may have been manifest in the eventual reduction in correlation in the long crisis period observed across all African markets (except South Africa).

4. *Disposition effect*

In the introduction to Section 6.6, I argued that the *disposition effect* may delay investors selling off stocks, as part of a loss-aversion bias, until *market capitulation* occurs. This could potentially account for some of the differences in correlation observed if capitulation occurred at different points of time in US and in Africa.

From an African perspective, I suggest that capitulation may have occurred relatively early in the crisis as is evident from the early increases in volatility relative to the US market. The observed changes in correlations can be interpreted as showing that the sell-off was quicker in Africa. This could possibly have occurred because of a faster reaction to social networking effects or, alternatively, due to differences in African investors' risk profiles in comparison with developed-market investors' attitudes to risk. If we refer back to the prospect theory (Section 2.5.1.1), we can interpret African investors as being more risk-averse, in that they cash in their profits early; as such, we see volatility in these markets increasing at the onset of the crisis. This behaviour could be amplified by the specific individuals who are the key opinion-formers within investor social networks (common in African institutional investors) offering advice to selloff in order to avoid further losses.

5. *Noise trading*

As discussed in Section 6.6.1, information is vital in financial markets and the lack of access to relevant or high quality information creates room for *noise trading*. Although financial integration mitigates information asymmetries (Schmukler 2004), the segmentation of African markets from the world market (i.e. the weakness of the relationship between markets (see: Hatemi-J and Morgan 2007, Bekaert et al. 2011, Berger, Pukthuanthong and Yang 2011)) would suggest information may get into African markets at a lower speed than to developed markets. In such circumstances investors are faced with information problems and the result can be that herding behaviour develops.

Other vectors of noise trading that might have possibly played important roles in African markets are *social influence* and *networking effects* (Gai and Kapadia 2010, Olsen 2004). It has been reported that African markets are characterised by the concentration of trading in few stocks and the dominance of a few companies on their exchanges (Allen, Otchere and Senbet 2011, Tafirenyika 2012). This would suggests that individuals who are in control of these stocks or even own some of the listed companies might have great influence on the markets; information coming from them will spread quickly, either as low quality or high quality information. Whichever way, this information can act as a vector of noise trading in the markets. This could, in turn, lead to herding behaviour and subsequent contagion effects even in uncorrelated markets, as evident in the African markets studied.

6.6.3 Behavioural biases in developed markets

1. ***Slow herding***

It can be noted from Table 6.2 that in the first sub-period of the crisis correlations actually fell between the US and; Canada, France, Italy, and showed no change in respect to the UK. This suggests that if herding did occur between developed markets the initial response was quite slow.

As noted above, Hwang and Salmon (2007) argued that herding can be a relatively slow process (see also Redhead, 2008). Herding commonly experienced in the presence of information is usually referred to as *rational herding*. Examples can be cited suggesting that it can be a slowly drawn-out process. Park and Sgroi (2009:1) reported that Robert Shiller suggested it occurred in the US housing market over a number of years, culminating in the 2007 crisis.

The slow speed of herding-based contagion effects spreading from the US to other developed markets can possibly be explained in terms of *social networking effects*. As identified in Section 6.6.1 above, the large number of high-status authoritative individuals in (the large) investor social networks may mean that it takes a considerable amount of time for a social mood-based consensus to be developed in such environments.

2. *Loss aversion*

Slow herding in developed markets may also be partly a function of loss aversion. As identified in the introduction to Section 6.6, loss aversion can lead to a disposition effect whereby investors hold off realising their losses until a final market capitulation ensues. It may very well be that the combination of the impact of slow decision-making in large social networks and a disposition effect may explain the relatively slow process of herding becoming instigated between developed markets. This may have also potentially interacted with status quo bias.

3. *Status quo bias*

It is difficult to provide a rational explanation for suggesting evidence of *status quo bias* in the developed markets while observing the behaviour of their correlations during the crisis. As such, it is best to consider the behaviour of investors with regards to timing in the stock markets. For this reason, I suggest status quo bias in respect to long-term investors, who are common in developed markets. Investors exhibit reluctance in changing the investments they have already made and are used to, regardless of their changing environment (Samuelson and Zeckhauser 1998). This, I suggest, could be the reason we saw no significant change in correlation during the crisis in highly integrated developed markets at its onset. It can be suggested that this bias is more prominent in Canada, France and Italy, which saw no contagion effect in the four sub-periods. In particular, Canada, which is the highest-correlated market with the US and also belongs in the same region, had only its long crisis correlation higher than the stable period correlation. This suggests strong reluctance to change during crisis.

As identified in Chapter 2, other biases influence investors to feel the status quo bias, but these biases, which include regret avoidance, drive for consistency, self-perception theory and illusion of control, need not occur at the same time. With this in mind, I suggest that the most relevant bias that led to the suggestion of the status quo bias in my sampled developed markets is regret avoidance, which is also related to loss aversion and rational herding. Another factor that could lead to the status quo bias occurring is the cost of information. Brown and Kagel (2009) suggested that status quo bias exists in an environment with a very low cost of identifying better-performing stocks. These types of environments, I suggest, are better attributed to developed-country markets.

6.6.4 Behavioural bias and the 2007-09 financial crisis: some conclusions

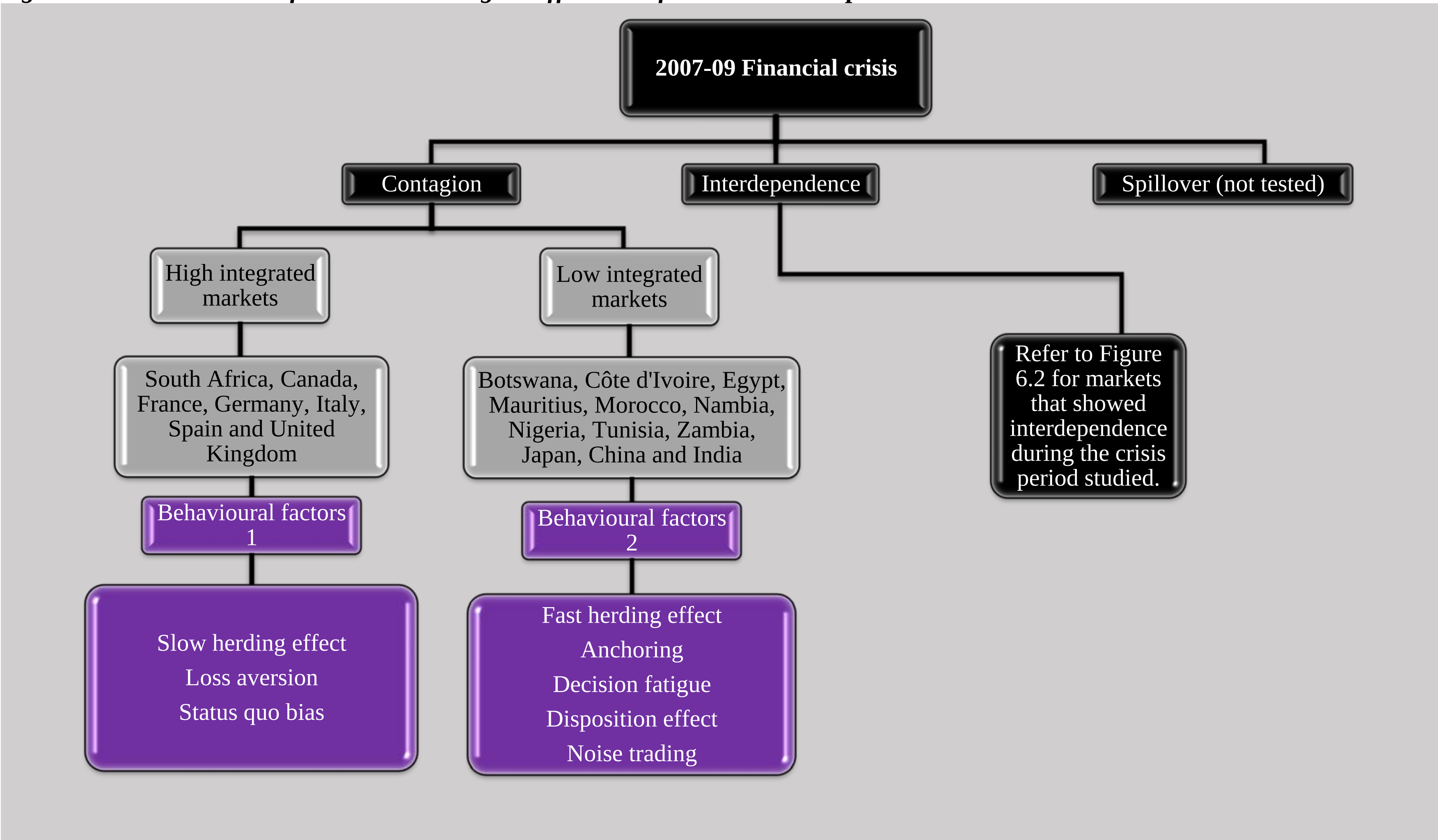
The problem any researcher faces when they try to apply behavioural bias theory to real-world examples is that many of these theories are strongly interconnected; there may indeed be a series of interaction effects between them, which makes disentangling different effects problematical.

What, however, appears clear from my work is that I have identified clear differences in the speed with which herding occurred in African markets and developed markets. I have also identified a clear theoretical reason why there should be differences in these speeds; specifically, that secondary information is developed at a far quicker rate in small social networks than in large social networks.

The existence of other behavioural biases/issues muddies the water somewhat in terms of distinguishing between herding in these two market types. *Disposition effect* is clearly an issue and, depending on the speed at which markets move from these to *capitulation*, will have a considerable impact on market correlations. There are clearly other issues that need to be taken into consideration as well such as differences between African and developed-market risk profiles, decision fatigue and noise trading. All of these issues make disentangling the difference between behavioural effects in African and developed markets problematical.

In Chapter 3, I developed a hypothesis that different behavioural factors would account for differences in contagion between African and developed markets. This was summarised as Figure 3.12. I now update this figure in light of the discussion of my thesis results in this chapter. This is shown in Figure 6.5 below.

Figure 6.5: Behavioural influences on contagion effects in African and developed markets



6.7 BEHAVIOURAL VS NON-BEHAVIOURAL CONTAGION CHANNEL DIFFERENCES BETWEEN AFRICAN AND DEVELOPED MARKETS: SOME FINAL CONCLUSIONS

In Section 6.5, I identified a number of non-behavioural factors that could possibly partially explain differences in contagion between African and developed countries. These included major differences between their respective banking systems, the strength of trade linkages and also different levels of stock market liquidity. In Section 6.6, I also identified possible behavioural reasons for the differences found. It may very well be that there are links between the behavioural and illiquidity issues (through the impact on social networking effects). I am sure that if I had looked at these relationships in more detail, links between banking system differences, market illiquidity and behavioural factors (specifically, speed of herding) would also become apparent.

Final analysis would suggest to me that the distinction between behavioural and non-behavioural channels of contagion is not a very useful distinction to make. There are a considerable number of interactions occurring between a number of factors and the role of this thesis has been to try to identify the most important factors that result in differences in contagion between US and African markets, and US and developed markets.

7 CONCLUDING SUMMARY, THESIS CONTRIBUTION, LIMITATIONS OF THE RESEARCH AND POTENTIAL FUTURE RESEARCH AREAS

7.1 INTRODUCTION

The key objective of this research has been to assess the impact of the 2007-09 financial crisis on financial contagion in African markets. As part of the process of identifying the potential channels down which the contagion event developed, I also made a comparative study of contagion in developed markets.

Contagion in this thesis is defined as “a significant increase in cross-market linkages resulting from a shock hitting one country or group of countries” (Forbes and Rigobon, 2002:2223).

The 2007-09 crisis was unique from a contagion perspective given that it was a truly global event that had a significant impact on most of the world’s financial markets. This has presented researchers with a unique opportunity to examine the impact of a single event on different types of markets (developed and emerging/frontier) and different geographical regions.

The 2007-09 crisis has given researchers the opportunity to explore in more detail the existing debate on the importance that the degree of *financial integration* plays in contagion events. Given that the crisis also enables researchers to explore the impact on different market types, it also presents the opportunity to examine other factors influencing the process of the transmission of crisis in greater depth. A number of previous papers in the contagion literature have identified *herding* as contributing to the transmission of crisis. My thesis developed a deeper and fuller behavioural finance-based analysis of the transmission process by exploring differences between African and developed markets. Past research has failed to identify the importance of individual behavioural biases on contagion events. Published research has also failed to identify the importance of the *speed of the herding process* in the transmission of contagion. This thesis explores both of these issues.

In comparing African (emerging/frontier) markets with developed markets the thesis is able to examine the importance of differences in financial integration on the contagion process. However, I submit that examining financial crisis contagion solely in terms of the level of integration alone is not sufficient. I argue that behavioural biases arising from human psychology play an important role in financial markets and that contagion also needs to be examined in the context of these.

7.2 SUMMARY OF THE MAIN FINDINGS OF THE THESIS

Theories of financial contagion, financial integration and behavioural biases were discussed in the literature review section (Chapter 2) as part of the process of identifying the gaps in the literature that research undertaken in this thesis could address. Within this chapter, I identified the potential novel contributions as: *1) examining alternative econometric methodologies; 2) applying contagion testing to both emerging and frontier African markets (an area of limited research in the literature); 3) examining contagion transmission channels from a behavioural finance perspective; and 4) examining differences in the contagion transmission channels of African and developed countries from a behavioural finance perspective.*

Chapter 3 discussed the dataset and developed two sets of statistical hypotheses. The dataset consisted of a sample of ten African markets (namely, Botswana, Côte d'Ivoire, Egypt, Mauritius, Morocco, Namibia, Nigeria, South Africa, Tunisia and Zambia), eight developed markets (namely, Canada, France, Germany, Italy, Japan, Spain, UK and the US) and two non-African markets included for comparative purposes, namely China and India. Using the VIX to identify potential contagion events, I identified what I describe as a long crisis period and four short sub-crisis periods. The statistical hypotheses set out in this chapter and subsequently tested in Chapters 4 and 5 were:

- That contagion occurred during the 2007-09 financial crisis across both developed and emerging/frontier African markets from 15 September 2008 to 15 October 2009 (long crisis period),
- That contagion occurred in the four short sub-crisis periods (15/09/2008-10/10/2008, 15/09/2008-17/10/2008, 15/09/2008-27/10/2008 and 15/09/2008-20/11/2008).

I also outlined a hypothesised theoretical model of contagion that would be examined in more detail in Chapter 6 in the context of the statistical findings from my research. This model was based on the hypothesis that (i) *contagion effects, if found, would differ between developed markets and emerging/frontier African markets on the basis of differences in the degree of integration between the sampled markets and the US, and (ii) that differences in the degree of integration level would result in different behavioural factors affecting the contagion transmission process.*

Chapters 4 and 5 detailed the econometric analysis undertaken in the thesis. A number of different approaches to the measurement of market correlation were undertaken for comparative purposes. These were used to investigate whether the crisis sourced in the US spread to African and developed country markets.

In Chapter 4, *constant correlation coefficient* based analysis in three variations was examined. First, I followed Forbes and Rigobon's (2002) approach as closely as possible using a single VAR system adjusted for heteroscedasticity bias. Second, I used raw log returns, also adjusted for heteroscedasticity in line with Forbes and Rigobon (2002). In the last variation of this approach, I made a statistical contribution to contagion literature by using two separate VAR systems divided into pre-crisis and crisis periods (which required no adjustment for heteroscedasticity). I concluded in this chapter that separate VAR systems approach is the preferred approach of the three.

In Chapter 5, the hypotheses tested in Chapter 4 were rerun using a *Dynamic Conditional Correlation coefficient* (DCC) based analysis. This was followed in Chapter 6 by a discussion of the relative merits of my preferred methodology in Chapters 4 and my methodology in Chapter 5. After identifying DCC as my preferred methodology, I discussed the main differences between the econometric results of African and developed markets from both a correlation and a contagion perspective.

Chapter 6 discussed the findings of the thesis from non-behavioural finance perspective and behavioural perspective and, finally, drew some conclusions in respect to differences between the process of contagion in African and developed markets.

7.2.1 Review of key findings

1. I found that the level of correlations between the US and African markets (except South Africa) were low before the crisis while all developed markets (except Japan) had high correlations before the crisis. China and India also had

low correlations before crisis. This finding enabled me to classify the sampled markets into low and highly (correlation of 40% or more) integrated markets. The low-integrated markets were Botswana, Côte d'Ivoire, Egypt, Mauritius, Morocco, Namibia, Nigeria, Tunisia, Zambia, Japan, China and India, while the highly integrated markets were Canada, France, Germany, Italy, Spain, UK and South Africa**.**

2. Initial examination of correlations indicated that the crisis had primarily a short-term effect in low-integrated markets and a long-term effect in highly integrated markets.
3. My results suggested that linkages between African markets and the US changed during the 2007-09 financial crisis. There was an initial increase in correlation during the crisis across all African markets (except Nigeria, Tunisia, Zambia and Mauritius because of statistical issues). These increases were significant, and in the form of contagion effects, in Botswana, Côte d'Ivoire, Egypt, Morocco, Namibia and South Africa.
4. I found an initial fall in correlation in the developed markets of Canada, France and Italy in sub-period 1. The correlation between the UK and US also saw no appreciable change between the pre-crisis period and sub-period 1. This indicated that the linkages between these developed markets remained the same at the onset of the crisis.
5. Examination of differences in correlations and contagion event from a behavioural finance perspective indicated that non-behavioural characteristics of African markets, such as illiquidity and size of the markets together with low levels of integration, amplified the effects of biases such as social/networking effects and mood in small markets. These biases then led to other active

behaviours in the African markets. I argued that the African markets experienced the following biases during the 2007-09 financial crisis: *fast herding, anchoring, decision fatigue, disposition effect* and *noise trading*. For the developed markets, where many sources of information exist, and social networks tend to be significantly larger, consensus is reached more slowly in social networks. I argued that this results in herding developing more slowly. I concluded that the following behavioural biases were found to influence contagion/interdependence in developed markets: *slow herding, loss aversion* and *status quo bias*.

7.3 REVIEW OF THESIS NOVEL CONTRIBUTIONS

I believe that this research has made the following novel contribution to the financial contagion literature:

- The thesis has added to our knowledge of contagion from the US to a broad cross-section of African markets.
- The thesis has compared the contagion effects found in African markets with those found in developed markets and has found differences in these group of markets.
- The thesis has contributed value to the analysis of the financial contagion from the perspective of behavioural finance theory both in African and developed markets. The principal finding being the differences in suggested behavioural biases affecting the two groups.
- The thesis has identified that the use of a DCC to measure correlation is the preferred statistical methodology, given the problems found in applying alternative methodologies.

7.4 LIMITATIONS OF THE RESEARCH

Even though my study was performed on ten African markets, a number of important markets are missing because of limitations in respect to my data sources. Missing countries included Ghana and Kenya. A lack of access to a full set of data on interest rates for African markets also meant that interest rates were excluded from my constant correlation regressions in Chapter 4. I believe, however, that this is of only minor importance given that Forbes and Rigobon (2002) identified interest rates as having no material impact on their results. I also faced issues in respect to data cleaning in my sampled markets. Given that national holidays differ across the globe I had a number of non-corresponding days that had to be eliminated from the sample. Given the length of the sample, however, I do not believe this to be a major issue.

7.5 FUTURE POTENTIAL AREAS OF RESEARCH

A number of potential areas for future research can be identified.

7.5.1 Spill-over effect

An extension of this research could be to test for contagion as a spill-over effect in the African markets. Morales and Andreosso-O'Callaghan (2010) reported that a shock in the US had a direct effect on Egypt and that this may have had secondary spill-over effects on other major African markets because of inter-linkages among African markets. In this thesis, South Africa was found to be the most strongly integrated with the US in my study, which suggests that spill-overs from South Africa might be a fruitful area for future study.

7.5.2 Sector-based contagion

A natural extension would be to investigate contagion within sectors from an African market perspective. Nigeria, for instance, is an oil exporter. This thesis found there to be no studies that examine whether a crisis in the oil sector creates a crisis in other market sectors in Africa. A study along these lines was carried out in respect to the US by Malik and Ewing (2009) in relation to volatility transmission between the oil sector and five US sectors. If this research is done with an African market, it will be an important contribution to the contagion literature.

Another potential sector-based investigation could be to investigate contagion from the banking sector of the US to the banking sectors of other countries. This initiative was first considered during this thesis. However, lack of sector data in the African markets impedes this research. Perhaps in advanced markets this would be a reasonable extension of this research.

7.5.3 Political crisis/uprisings in Africa

Political crises in Africa and the Middle East have inspired researchers such as Asongu (2011a) to investigate the impact of political unrest from a contagion perspective. Asongu's (2011a) research examined the Kenyan political crises. The author found some evidence of contagion. With this in mind and the recent waves of insurgency in Nigeria led by the militant group Boko Haram, one might wonder if contagion from Nigeria might be investigated. After a series of bomb blasts and mass killings that received little attention in the Western media, Boko Haram's profile was increased by the mass abduction of almost 300 girls in Chibok, Borno state of Nigeria on 14 April 2014 (BBC news). At the time of this research, the girls had been in captivity more than

100 days. A major question that could be posed subsequent to the abduction incident is whether or not the insurgency led to unexplained movement in Nigeria stock market and whether there was a contagion effect to other African markets? This is indeed an idea for a future research area.

8 REFERENCE LIST

4E Journal (2010) ‘A Behavioural View of how People make Financial Decisions’. *The Official Publication of the Financial Planning Association of Malaysia* 10 (4).

Aduda, J., Oduor, O. E., and Onwonga, M. (2012) ‘The Behaviour and Financial Performance of Individual Investors in the Trading Shares of Companies Listed at the Nairobi Stock Exchange, Kenya’. *Journal of Finance and Investment Analysis* 1 (3), 33-60.

AfDB/OECD (2008) ‘Nigeria’. *African Economic Outlook*, 509-519.

African Development Bank (2009) ‘Impact of the Global Financial Crisis and Economic Crisis on Africa’. *Working Paper Series* (9).

African Securities Exchange Association, ASEA (2009) *ASEA Year Book*.

African Securities Exchange Association, ASEA (2008) *ASEA Year Book*.

African Securities Exchange Association, ASEA (2007) *ASEA Year Book*.

Aghion, P., Bolton, P., and Dewatripont, M. (1999) ‘Contagious Bank Failures in a Free Banking System’.

Agyei-Ampomah, S. (2011) ‘Stock Market Integration in Africa’. *School of Management, University of Surrey, Guildford*, 1-22.

Ahnert, T. and Bertsch, C. (2014) ‘A Wake-Up Call Theory of Contagion’.

Allen, F., Otchere, I., and Senbet, L. (2011) ‘African Financial Systems: A Review’. *Review of Development Finance.*

Ampomah, S. A. (2008) ‘An Empirical Examination of the Inter-Linkages between African Stock Markets’. University of Surrey, Guildford.

Ang, A., Bekaert, G., and Liu, J. (2005) ‘Why Stocks may disappoint’. *Journal of Financial Economics* 76.

Aparicio, F., and Estrada, J. (1997) ‘Empirical Distributions of Stock Returns: Scandinavian Securities Markets, 1990-95’.

Arestis, P., Caporale, G., Cipollini, A., and Spagnolo, N. (2005) ‘Testing for Financial Contagion between Developed and Emerging Markets during the 1997 East Asian Crisis’.

Asai, M. (2013) ‘Heterogeneous Asymmetric Dynamic Conditional Correlation Model with Stock Return and Range’. *Journal of Forecasting* 32 (5), 469-480.

Asch, S. E. (1952) *Social Psychology*. New York: Prentice Hall.

Asongu, S. A. (2011b) ‘Globalisation, Financial Crisis and Contagion: Time-Dynamic Evidence from Financial Markets of Developing Countries’.

Asongu, S. A. (2011a) ‘Political Crises and Risk of Financial Contagion in Developing Countries: Evidence from Africa’.

Babajide, A. A. and Adetiloye, K. A. (2012) ‘Investors’ Behavioural Biases and the Security Market: An Empirical Study of the Nigerian Security Market’. *Accounting and Finance Research* 1 (1), 219-229.

Baig, T. and Goldfajn, I. (1999) ‘Financial Market Contagion in the Asian Crisis’. *International Monetary Fund, Staff Papers* 46 (2).

Baker, H. K. and Nofsinger, J. R. (2002) ‘Psychological Biases of Investors’. *Financial Services Review* 11 (2), 97-116.

Banerjee, A. (1992) ‘A Simple Model of Herd Behaviour’. *Quarterly Journal of Economics* 107, 797-818.

Barber, B. M., Lee, Y., Liu, Y., and Odean, T. (2007) ‘Is the Aggregate Investor Reluctant to Realise Losses: Evidence from Taiwan’. *European Financial Management* 13 (3), 423-447.

Barberis, N., Shleifer, A., and Vishny, R. (1998) ‘A Model of Investor Sentiment’. *Journal of Financial Economics* 49.

Barsky, R. B. (2009) ‘The Japanese Bubble: A ‘Heterogeneous’ Approach’. *NBER Working Paper Series* (15052).

Bartlett, D. (2008) ‘Fallout of the Global Financial Crisis’. *The Worldwide Audit, Tax and Consulting Network.*

Baxter, M. and Jermann, U., J. (1997) ‘The International Diversification Puzzle is Worse than You Think’. *American Economic Review* 87, 170-180.

Becker, R., Clements, A., and McClelland, A. (2009) ‘The Jump Component of S&P500 Volatility and VIX Index’. *Journal of Banking and Finance* 33 (6), 1033-1038.

Beirne, J. and Gieck, J. (2012) ‘Interdependence and Contagion in Global Asset Markets’. *European Central Bank Working Paper Series* (1480).

Beirne, J., Caporale, G., Schulze-Ghattas, M., and Spagnolo, N. (2009) 'Volatility Spillovers and Contagion from Mature to Emerging Stock Markets'. *Deutsches Institut Für Wirtschaftsforschung, Discussion Paper* (873).

Bekaert, G., Harvey, C., Lundblad, C. T., and Siegel, S. (2011) 'What Segments Equity Markets?' *Review of Financial Studies* 24 (12), 3841-3890.

Bekaert, G., Harvey, C., and Ng, A. (2005) 'Market Integration and Contagion'. *Journal of Business* 78 (1), 39-70.

Beltratti, A. and Stulz, R. (2012) 'The Credit Crisis around the Globe: Why did some Banks Perform Better?' *Journal of Financial Economics* 105, 1-17.

Berger, D., Pukthuanthong, K., and Yang, J. (2011) 'International Diversification with Frontier Markets '. *Journal of Financial Economics* 101 (1), 227-242.

Bikhchandani, S. and Sharma, S. (2001) 'Herd Behaviour in Financial Markets'. *International Monetary Fund Staff Papers* 47 (3), 279-310.

Billio, M. and Pelizzon, L. (2003) 'Contagion and Interdependence in Stock Markets: Have they been misdiagnosed?' *Journal of Economics and Business* 55, 405-426.

Blasco, N., Corredor, P. and Ferreruela, S. (2011) 'Detecting Intentional Herding: What Lies Beneath Intraday Data in the Spanish Stock Market'. *Journal of the Operational Research Society* 62 (6), 1056-1066

Boamah, N. (ed.) (2014) *Proceedings of 25th International Business Research Conference*. 'Global Integration of African Stock Markets'. Held 13-14 January 2014 at Cape Town, South Africa.

Bollerslev, T., Chou, R. Y., and Kroner, K. F. (1992) ‘ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence’. *Journal of Econometrics* 52, 5-59.

Boyer, B. H., Kumagai, T., and Yuan, K. (2006) ‘How do crises spread? Evidence from accessible and inaccessible stock indices’. *Journal of Finance* 61, 957-1003.

Brown, A., L. and Kagel, J., H. (2009) ‘Behaviour in a Simplified Stock Market: The Status Quo Bias, the Disposition Effect and the Ostrich Effect’. *Annals of Finance* 5 (1), 1-14.

Brunnermeier, M., K. (2008) ‘Deciphering the Liquidity and Credit Crunch 2007-08’. *National Bureau of Economic Research Working Paper* (14612).

Bryman, A. and Bell, E. (2011) ‘Ethics in Business Research’, *Business Research Methods.* Third edn: Oxford University Press.

Bryman, A. and Bell, E. (2007) *Business Research Methods*. Second edn: Oxford University Press.

Bunya, R. (2003) ‘Africa’s Equity Markets - A Synopsis’. in *UNDP African Stock Exchanges Handbook*.

Burnham, K., P. and Anderson, D., R. (2004) ‘Multimodel Inference Understanding AIC and BIC in Model Selection’. *Sociological Methods & Research* 33 (2), 261-304.

Calvo, G., A. and Mendoza, E. (1998) ‘Rational Herd Behaviour and the Globalization of Securities Markets’. *College Park*, Maryland, University of Maryland.

Calvo, G. and Mendoza, E. (2000) ‘Rational Contagion and the Globalization of Security Markets’. *Journal of International Economics* 51, 79-113.

Caporale, G., Cipollini, A., and Spagnolo, N. (2005) ‘Testing for Contagion: A Conditional Correlation Analysis’. *Journal of Empirical Finance* 12, 476-489.

Carswell, J. (1960) ‘The South Sea Bubble’.

Čekauskas, K. and Liatukas, V. (2011) *Behavioural Biases of the Disposition Effect and Overconfidence and their Impact on the Estonian Stock Market.* [Online] Bachelor Thesis: Stockholm School of Economics in Riga.

Chen, G., Kim, K., Nofsinger, J., and Rui, O. (2007) ‘Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors’. *Journal of Behavioural Decision-Making* 20 (4), 425-451.

Chen, G., Kim, K. A., Nofsinger, J. R., and Rui, O. M. (2005) ‘Behaviour and Performance of Emerging Market Investors: Evidence from China’.

Cheng, H. and Glascock, J. L. (2006) ‘Stock Market Linkages Before and After the Asian Financial Crisis: Evidence from Three Greater China Economic Area Stock Markets and the US’. *Review of Pacific Basin Financial Markets and Policies (RPBFMP)* 9 (2), 297.

Chenguel, B. M. (2014) ‘The Subprime Crisis Contagion Effect on Developed Countries’. *Journal of Business and Management Research* 3, 61-70.

Cheung, L., Tam, C., and Szeto, J. (2009) ‘Contagion of Financial Crises: A Literature Review of Theoretical and Empirical Frameworks’. *Hong Kong Monetary Fund, Research Note 02.*

Chiang, T. C., Jeon, B. N, and Li, H. (2007) ‘Dynamic Correlation Analysis of Financial Contagion: Evidence from Asian Markets’. *Journal of International Money and Finance* 26 (7), 1206-1228.

Ciarlone, A. and Piselli, P. (2009) ‘Emerging Markets’ Spreads and Global Financial Conditions’. *International Financial Markets, Institutions and Money* 19, 222-239.

Cipriani, M. and Guarino, A. (2010) ‘Herd Behaviour and Contagion in Financial Markets’. *Institute for International Economic Policy.*

Claessens, S. and Forbes, K. (2004) ‘International Financial Contagion: The Theory, Evidence and Policy Implications’.

Coeurdacier, N. and Rey, H. (2011) ‘Home Bias in Open Economy Financial Macroeconomics’. *London Business School, CEPR and NBER.*

Collins, D. and Biekpe, N. (2003) ‘Contagion and Interdependence in African Stock Markets’. *The South African Journal of Economics* 71:1.

Constantinos, A. (2010) *Three Essays in Behavioural Finance: An Examination into Non- Bayesian Investment Behaviour*. [Online] Doctor of Philosophy thesis or dissertation. Durham theses: Durham University.

Consulate General of India, Chicago. (2014) *India – U.S. Trade* [online]. available from <http://indianconsulate.com/page/display/92/33> [17 August 2014].

Cooper, M. J., Dimitrov, O., and Rau, P. (2001) 'A Rose.Com by any Other Name'. *Journal of Finance* 56 (6), 2371-2388.

Corsetti, G., Pesenti, P., and Roubini, N. (1999) 'What Caused the Asian Currency and financial crisis?' *Japan and the World Economy* 11 (3), 305-373.

Coval, J., Hirshleifer, D., and Teoh, S. H. (2004) 'Self-Deception and Deception in Capital Markets'.

Crotty, J. (2009) 'Structural Causes of the Global Financial Crisis: A Critical Assessment of the 'new Financial Architecture''. *Cambridge Journal of Economics* 33, 563-580.

Cuñado, J., Gil-Alana, L. A., and Perez de Gracia, F. (2008) 'Stock Market Volatility in US Bull and Bear Markets'. *Journal of Money, Investment and Banking* (1), 24-32.

D'Anne, H. (2012) 'VIX and VIX Futures Pricing Algorithms: Cultivating Understanding'. *Modern Economy* 3 (3), 284-294.

Daniel, K. and Titman, S. (2000) 'Market Efficiency in an Irrational World'. *National Bureau of Economic Research Working Paper* (7489).

DeMarzo, P., Vayanos, D., and Zwiebel, J. (2003) 'Persuasion Bias, Social Influence, and Unidimensional Opinions'. *Quarterly Journal of Economics* 118 (3), 909-968.

Diamond, D. W. and Dybvig, P. H. (1983) 'Dybvig Bank Runs, Deposit Insurance, and Liquidity'. *The Journal of Political Economy* 91 (3), 401-419.

Dionne, G., Pacurar, M., and Zhou, X. (2014) 'Liquidity-Adjusted Intraday Value at Risk Modeling and Risk Management: An Application to Data from Deutsche Börse'.

Dornbusch, R., Park, C. Y., and Claessens, S. (2000) 'Contagion: Understanding how it spreads and how it can be stopped'. *The World Bank Research Observer* 15 (2), 177-197.

Drazen, A. (1999) 'Political Contagion in Currency Crises'. *National Bureau of Economic Research, Cambridge Mass* Working Paper 7211.

Duan, J. and Yeh, C. (2008) 'Jump and Volatility Risk Premiums Implied by VIX'.

Duffie, D. and Pan, J. (1997) 'An Overview of Value at Risk'.

Dungey, M., Fry, R., Gonzalez-Hermosillo, B., and Martin, V. (2005a) 'Empirical Modelling of Contagion: A Review of Methodologies'. *Quantitative Finance* 5 (1), 9-24.

Dungey, M., Fry, R., Gonzalez-Hermosillo, B., and Martin, V. (2005b) 'Sampling Properties of Contagion Tests'.

Dungey, M. and Zhumabekova, D. (2001) 'Testing for Contagion using Correlations: Some Words of Caution'. *Working Paper PB01-09. Centre for Pacific Basin Monetary and Economic Studies, Economic Research Department,* Federal Reserve Bank of San Francisco.

Dungey, M. and Martin, V. (2000) 'Measuring Contagion in the East Asian Currency Crisis'. *Australian National University Working Paper,* Canberra.

Edwards, W. (1968) ‘Conservatism in Human Information Processing’ in *Formal Representation of Human Judgment*. ed. by Kleinmutz, B. : John Wiley and Sons, 17-52.

Edwards, S. (2000) ‘Contagion ’. *The World Economy* 23 (7), 873-900.

EIB (2013) ‘Banking in Sub-Saharan Africa: Challenges and Opportunities’. *European Investment Bank.*

Eichengreen, B. and Rose, A. (1999) ‘Contagious Currency Crises: Channels of Conveyance ’. in *Changes in Exchange Rates of Rapidly Developing Countries*. ed. by Ito, T. and Krueger, A., O. : University of Chicago Press.

Eichengreen, B., Rose, A., and Wyplosz, C. (1996) ‘Contagious Currency Crises’. *Scandinavian Journal of Economics* 98, 463-484.

England, A. (2014) *International Banks Ramp up Presence in Africa* [online]. available from <http://www.ft.com/intl/cms/s/0/600b6880-0fa0-11e1-a36b-00144feabdc0.html#axzz39invOynp> [26 August 2014].

Engle, R. F. and Sheppard, K. (2001) ‘Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH’. *NBER Working Paper* (8554).

Engle, R. F. and Ng, V. K. (1993) ‘Measuring and Testing the Impact of News on Volatility’. *Journal of Finance* 48 (5), 1749-1778.

Engle, R. F. (2002) ‘Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroscedasticity Models’. *Journal of Business and Economic Statistics* 20, 339-350.

Ernst and Young (2014) *Africa Attractiveness Survey 2014* [online]. available from <www.ey.com/ZA/en/Issues/Business-environment/EY-africa-attractiveness-survey-2014> [23 August 2014].

Errunza, V., R. (1994) ‘Emerging Markets: Some New Concepts ‘. *Journal of Portfolio Management*, 82-87.

Essaadi, E., Jouini, J., and Khallouli, W. (2009) ‘The Asian Crisis Contagion: A Dynamic Correlation Approach Analysis’. *Panoeconomicus* 2, 241-260.

Evanoff, D., Kaufman, G., and Malliaris, A. (2012) ‘Asset Price Bubbles: What are the Causes, Consequences, and Public Policy Options?’ *Chicago Fed Letter*.

Fielding, D. and Stracca, L. (2007) ‘Myopic Loss Aversion, Disappointment Aversion, and the Equity Premium Puzzle’. *Journal of Economic Behaviour and Organisation* 64.

Fischer, B. (1986) ‘Noise’. *The Journal of Finance* 41 (3), 529-543.

Forbes, K. (2012) ‘The “Big C”: Identifying and Mitigating Contagion ’. *Jackson Hole Symposium, Hosted by the Federal Reserve Bank of Kansas City*, 23-87.

Forbes, K. (2004) ‘The Asian Flu and Russian Virus: The International Transmission of Crises in Firm-Level Data’. *Journal of International Economics* 63, 59-92.

Forbes, K. and Rigobon, R. (1999) ‘Measuring Contagion: Conceptual and Empirical Issues’. *Mimeo,* MIT.

Forbes, K. and Rigobon, R. (2002) ‘No Contagion, Only Interdependence: Measuring Stock Market Co-Movements’. *Journal of Finance* 57 (5), 2223-2261.

Forgas, J. P. (1995) ‘Mood and Judgment: The Affect Infusion Model (AIM)’. *Psychological Bulletin* (117).

Fortune, P. (1993) ‘Stock Market Crashes: What Have We Learned from October 1987?’ *New England Economic Review.*

Frehen, R. G., Goetzmann, W. N., and Rouwenhorst, K.G. (2011) ‘New Evidence on the First Financial Bubble’.

French, D. (2006) ‘The Dutch Monetary Environment during Tulipmania’. *The Quarterly Journal of Austrian Economics* 9 (1), 3-14.

Fry-McKibbin, R., Martin, V., and Tang, C. (2013) ‘Financial Contagion and Asset Pricing’. *Centre for Applied Macroeconomic Analysis.* The Australian National University.

Gai, P. and Kapadia, S. (2010) ‘Contagion in Financial Networks’. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science* 466(2120), 2401-2423.

Galesi, A. and Sgherri, S. (2009) ‘Regional Financial Spillovers across Europe: A Global VAR Analysis’. *IMF Working Paper 09/23.*

Garber, P. (1990) ‘Famous First Bubbles’. *Journal of Economic Perspectives* 42 (2), 35-54.

Garber, P. (1989) ‘Tulipmania’. *The Journal of Political Economy* 97 (3), 535-560.

Gardiner, K. (2012) ‘Euro Fatigue’. *Wealth and Investment Management, Global Research & Investments. COMPASS, Barclays.*

Ghalanos, A. (2013) ‘RMGARCH: Multivariate GARCH Models’.

Gilmore, C. and McManus, G. (2002) ‘International Portfolio Diversification: US and Central European Equity Markets’. *Emerging Markets Review* 3, 69-83.

Glosten, L. R., Jagannathan, R., and Runkle, D., E. (1993) ‘On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks’. *Journal of Finance* 48 (5), 1779-1801.

Goetzmann, W., Li, L., and Rouwenhorst, K.G. (2004) ‘Long-Term Global Market Correlations’. *Yale International Center for Finance.*

Goldfajn, I. and Valdes, O. R. (1997) ‘Capital Flows and the Twin Crises: The Role of Liquidity’. *Working Paper 97/87, International Monetary Fund, Washington, D.C.*

Goldstein, I., and Pauzner, A. (2004) ‘Contagion of Self-Fulfilling Financial Crises due to Diversification of Investment Portfolios’. *Journal of Economic Theory* 119, 151–183

Green, H. (2011) *Avoiding the Dreaded Decision Fatigue* [online]. Available from <http://www.forbes.com/sites/work-in-progress/2011/09/07/avoiding-the-dreaded-decision-fatigue/> [26 August 2014].

Haas, M., and Pigorsch, C. (2007) ‘Financial Economics, Fat-tailed Distributions’.

Hansen, B. E. (2001) ‘The New Econometrics of Structural Change: Dating Breaks in U. S. Labor Productivity’. *Journal of Economic Perspectives* 15, 117-128.

Harman, D. (2009) ‘Judgment and Decision-Making: Psychological Perspectives’. *British Psychological Society and Blackwell Publishing Ltd.*

Harvey, C. (1995) ‘Predictable Risk and Returns in Emerging Markets’. *The Review of Financial Studies* 8 (3), 773-816.

Hatemi-J, A. and Morgan, B. (2007) ‘Liberalized Emerging Markets and the World Economy: Testing for Increased Integration with Time-Varying Volatility’. *Applied Financial Economics* 17, 1245-1250.

Hede, P. D. (2012) *Financial Decision-Making and Investor Behaviour*. Ventus Publishing ApS.

Henker, J., Henker, T., and Mitsios, A. (2003) ‘Do Investors Herd Intraday in the Australian Equities Market?’

Hentschel, L. (1995) ‘All in the Family: Nesting Symmetric and Asymmetric GARCH Models’. *Journal of Financial Economics* 39, 71-104.

Hermandez, L. F. and Valdes, R. O. (2001) ‘What Drives Contagion: Trade, Neighbourhood or Financial Links?’ *International Reviews of Financial Analysis* 10, 203-218.

Higgins, M. L. and Bera, A. K. (1992) ‘A Class of Nonlinear ARCH Models’. *International Economic Review* 33, 137-158.

Hirshleifer, D. (2001) ‘Investor Psychology and Asset Pricing’. *Journal of Finance* 56, 1533-1597.

Holmes, P., Kallinterakis, V., and Ferreira, M. L. (2011) ‘Herding in a Concentrated Market: a Question of Intent’. *European Financial Management.*

Hon, M. T., Strauss, J., and Yong, S. (2004) ‘Contagion in Financial Markets after September 11 - Myth or Reality? ‘. *Journal of Financial Research* 27, 95-114.

Horta, P., Mendes, C., and Vieira, I. (2008) ‘Contagion Effects of the US Subprime Crisis on Developed Countries’. *CEFAGE-UE Working Paper.*

Hosking, J. R. (1980) ‘The Multivariate Portmanteau Statistic’. *Journal of the American Statistical Association* 75 (371), 602-608.

Hovde, J. G. (2014) ‘Behavioural Finance, a Challenge to the EMH’. in *Modern Portfolio Theory and Behavioural Finance*. ed. by Anon.

Huang, H. (2000) ‘Financial Contagion: ABC Channels’. *IMF Research Bulletin* 1 (2).

Huang, H. and Xu, C. (2000) ‘Financial Institutions, Financial Contagion, and Financial Crises’. *IMF Working Paper* (92).

Huang, W. and Chen, Z. (2014) ‘Modelling Financial Crises and Contagion’. *Division of Economics*, Nanyang Technological University Singapore.

Hwang, S. and Salmon, M. (2007) ‘Sentiment and Beta Herding’. *Warwick Business School.*

Inci, A., Li, H., and McCarthy, J. (2011) ‘Financial Contagion: A Local Correlation Analysis’. *Research in International Business and Finance* 25 (1), 11-25.

Inclán, C. and Tiao, G., C. (1994) ‘Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance’. *Journal of the American Statistical Association* 89, 913-923.

Irving, W. (2008) ‘A Time of Unexampled Prosperity: The Great Mississippi Bubble’. *EIR. Economic History*, 38-47.

Ishikawa, T. (2011) ‘Japan’s Bubble, Deflation, and Long-Term Stagnation: Review of an Oral History Study’. *Economic and Social Research Institute Note* (19).

Jeanne, O. (1998) *The International Liquidity Mismatch and the New Architecture*.

Jefferis, K., and Tacheba, A. Botswana Financial Sector Review (2009/2010).

Johansen, S. (1991) ‘Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models’. *Econometrica* 59 (6), 1551-1580.

Kahneman, D., Slovic, P., and Tversky, A. (1982) *Judgment under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press.

Kahneman, D. and Tversky, A. (1979) ‘Prospect Theory: An Analysis of Decision under Risk’. *Econometrica: Journal of the Econometric Society* 47 (2), 263-292.

Kaminsky, G. L., Reinhart, C. M., and Vegh, C. A. (2003) ‘The Unholy Trinity of Financial Contagion’. *National Bureau of Economic Research, Working Paper*.

Kaminsky, G. L., Lyons, R. K., Schmukler, S. (2001, August) ‘Mutual Fund Investment in Emerging Markets: An Overview’. World Bank Economic Review Volume 15 (2), 315-339.

Kaminsky, G. and Reinhart, C. (2000) ‘On Crises, Contagion and Confusion’. *Journal of International Economics* 51 (1), 145-168.

Kaminsky, G. L. and Reinhart, C. M. (1999) ‘Bank Lending and Contagion: Evidence from the Asian Crisis’. *Working Paper, National Bureau of Economic Research.*

Kaminsky, G. L. and Reinhart, C. M. (1998) ‘Financial Crises in Asia and Latin America: Then and Now’. *American Economic Review, American Economic Association* 88 (2), 444-448.

Kanas, A. (1998) ‘Linkages between the US and European Equity Markets: Further Evidence from Cointegration Test’. *Applied Financial Economics* 8 (6), 607-614.

Kang, S. H. and Yoon, S. (2011) ‘The Global Financial Crisis and the Integration of Emerging Stock Markets in Asia’. *Journal of East Asian Economic Integration* 15 (4), 49-73.

Kasekende, L., Mlambo, K., Murinde, V., and Zhao, T. (2009) ‘Restructuring for Competitiveness: The Financial Services Sector in Africa’s Four Largest Economies’. in *World Economic Reform*. ed. by Anon, 49-81.

Kassim, H. S. (2013) ‘The Global Financial Crisis and the Integration of Islamic Stock Markets in the Developed and Developing Countries’. *Asian Academy of Management Journal of Accounting and Finance* 9 (2), 75-94.

Khalid, A. and Rajaguru, G. (2006) ‘Financial Market Contagion or Spill-Overs Evidence from Asian Crisis using Multivariate GARCH Approach’.

Khawaja, H. A., Bhutto, N. A., and Naz, S. (2013) ‘Investors’ Behavioural Biases and the Stock Market Development: An Empirical Study of the Pakistani Stock Market’. in *Handbook on the Economic, Finance and Management Outlooks*. ed.

by Anon Proceedings Book of ICEFMO, 2013, Malaysia: PAK Publishing Group, 636-642.

Kimmel, A. J. (2004) 'Rumours and the Financial Marketplace'. *Journal of Behavioural Finance* 5.

King, M. and Wadhwani, S. (1990) 'Transmission of Volatility between Stock Markets'. *Review of Financial Studies* 3 (1), 5-33.

Kirkpatrick II, C. D. and Dahlquist, J. (2010) 'Technical Analysis: The Complete Resource for Financial Market Technicians'. *FT Press.*

Kittiakarasakun, J. and Tse, Y. (2011) 'Modeling the Fat Tails in Asian stock markets'. *International Review of Economics and Finance* 20 (3), 430-440.

Kodres, L. and Pritsker, M. (2002) 'A Rational Expectations Model of Financial Contagion.' *The Journal of Finance* 57 (2), 769-799.

Kodres, L. and Pritsker, M. (1996) 'Directionally Similar Position Taking and Herding by Large Futures Market Participants'. *in Risk Measurement and Systematic Risk: Proceedings of a Joint Central Bank Research Conference, Board of Governors of the Federal Reserve*, 221-272.

Kraay, A. and Ventura, J. (eds.) (2007) *G7 Current Account Imbalances: Sustainability and Adjustment*. 'The Dot-Com Bubble, the Bush Deficits, and the U.S. Current Account'. Held June 1-2, 2005: University of Chicago Press.

Kremer, S. (2010) 'Herding of Institutional Traders'. *Free University Berlin* 1-44

Kudryavtsev, A., Cohen, G., and Hon-Snir, S. (2013) ‘Rational” Or “Intuitive”: Are Behavioural Biases Correlated Across Stock Market Investors?’ *Contemporary Economics* 7 (2), 31-53.

Lakonishok, J., Shleifer, A., and Vishny, R. (1992) ‘The Impact of Institutional Trading on Stock Prices’. *Journal of Financial Economics* 32, 23-43.

Lamoureux, C. G. and Lastrapes, W. D. (1990) ‘Heteroscedasticity in Stock Returns Data: Volume versus GARCH Effects’. *The Journal of Finance* 45, 221-229.

Lau, L. J. and Li, K. (2001) ‘Lessons from the East Asian Currency Crisis’. *Stanford University*.

Lee, H., Wu, H., and Wang, Y. (2007) ‘Contagion Effect in Financial Markets after the South-East Asia Tsunami’. *Research in International Business and Finance* 21, 281-296.

Lee, S. B. and Kim, K. J. (1993) ‘Does the October 1987 Crash Strengthen the Co-Movements among National Stocks Markets?’ *Review of Financial Economics* 3 (1), 89-102.

Levine, R. and Zervos, S. (1998) ‘Stock Markets, Banks, and Economic Growth’. *The American Economic Review* 88 (3), 537-558.

Li, W. K. and McLeod, A. I. (1981) ‘Distribution of the Residual Autocorrelation in Multivariate ARMA Time Series Models’. *Journal of the Royal Statistical Society, Series B.* 43 (2), 231-239.

Liew, V. K-S. (2004) ‘Which Lag Length Selection Criteria should we Employ?’. *Economics Bulletin* 3 (33), 1-9.

Lin, J., Dinh, H., and Im, F. (2010) ‘United States-China External Imbalance and the Global Financial Crisis’. *China Economic Journal* 3 (1), 6-23.

Lintenr, G. (1998) ‘Behavioural Finance: Why Investors make Bad Decisions’. *The Planner* 13 (1), 7-8.

Ljung, G. M. and Box, G. E. P. (1978) ‘On a Measure of a Lack of Fit in Time Series Models’. *Biometrika* 65, 297-303.

Lo, W. A. (2011) ‘Fear, Greed, and Financial Crises: A Cognitive Neurosciences Perspective’.

Longin, F. and Solnik, B. (1995) ‘Is the Correlations of International Equity Returns Constant: 1960–1990?’ *Journal of International Money and Finance* 14 (1), 3-26.

Lowies, G., Hall, J., and Cloete, C. (2013) ‘The Influence of Frame Dependence on Investment Decisions made by Listed Property Fund Managers in South Africa’. *Journal of Economics and Behavioural Studies* 5 (11), 805-814.

Lutje, T., and Menkhoff, L. (2003) ‘Risk Management, Rational Herding and Institutional Investors: A Macro View’. *University of Hannover Discussion Paper* 285.

Mackay, C. (2011) ‘Behavioural Finance and Technical Analysis as the Solution to Fundamental Analysis and the Efficient Market Hypothesis: From the Preface to the 1852 Edition of Extraordinary Popular Delusions and the Madness of Crowds'. *United-ICAP*.

Magnus, F. J. (2008) 'Capital Market Efficiency: An Analysis of Weak Form Efficiency on the GSE'. *Journal of Money, Investment and Banking*, 1-8.

Malik, S. U., and Elahi, M. A. (2014) 'Analysis of Herd Behavior Using Quantile Regression: Evidence from Karachi Stock Exchange (KSE)'. 55322

Malik, F. and Ewing, B. (2009) 'Volatility Transmission between Oil Prices and Equity Sector Returns'. *International Review of Financial Analysis* 18, 95-100.

Malik, I. N., Ullah, S., Azam, K., and Khan, A. (2009) 'The Impact of Recent Global Financial Crisis on the Financial Institutions in the Developing Countries: Global Perspectives'. *International Review of Business Research Papers* 5 (5), 85-95.

Malkiel, B. G. (2010) 'Bubbles in Asset Prices'. *CEPS Working Paper, Princeton University.*

Masetti, O. and Mihr, A. (2013) 'Capital Markets in Sub-Saharan Africa'. *Research Briefing for Deutsche Bank.*

Masih, A. and Masih, R. (1997) 'Dynamic Linkages and the Propagation Mechanism Driving Major International Stock Markets: An Analysis of the Pre- and Post-Crash Eras'. *The Quarterly Review of Economics and Finance* Volume 37 (4, Fall), 859-885.

Massa, I. (2009) 'Stock Markets in Africa: Bidding for Growth amid Global Turmoil'. *Overseas Development Institute. in Opinion* (134).

Massacci, D. (2007) ‘Identification and Estimation in an Incoherent Model of Contagion’.

Masson, P. R. (1998) ‘Contagion: Monsoonal Effects, Spill-Overs, and Jumps between Multiple Equilibria’. *International Monetary Fund, Working Paper 98/142.* Washington DC.

Mathur, I., Gleason, K., Dibooglu, S., and Singh, M. (2002) ‘Contagion Effects from the 1994 Mexican Peso Crisis: Evidence from Chilean Stocks ’. *The Financial Review* 37, 17-34.

Mendoza, E. and Quadrini, V. (2010) ‘Financial Globalization, Financial Crises and Contagion’. *Journal of Monetary Economics* 57, 24-39.

Meric, G., Leal, R., Ratner, M., and Meric, I. (2001) ‘Co-Movements of U.S. and Latin American Equity Markets before and After the 1987 Crash’. *International Review of Financial Analysis* 10 (3), 219-235.

Mobarek, A., Muradoglu, G., and Mollah, S. (2014) ‘Determinants of Time-Varying Co-Movements among International Stock Markets’.

Morales, L. and Andreosso-O’Callaghan, B. (2010) ‘The Global Financial Crisis: World Market Or Regional Contagion Effects?’ *Conference Papers, Dublin Institute of Technology.*

Moser, T. (2003) ‘What Is International Financial Contagion?’ *International Monetary Fund, International Finance* 6 (2), 157-178.

Moussalli, C. B. (2007) ‘Financial Crises, Panic and Contagion: Evidence from a Cross-Country Comparison using Two Time Frames’. *Journal of Business and Public Affairs* 1 (2).

Mulyadi, M. S. and Anwar, Y. (2012) ‘Return and Volatility Spillover across USA and Europe (Study of American and EU Crisis Period)’. *African Journal of Business Management* 6 (19), 5916-5926.

Myers, D. (1989) *Psychology*. 2nd edn. New York: Worth Publishers, Inc.

Nellor, D. (2008) ‘The Rise of Africa’s “Frontier” Markets, Finance and Development’. *A Quarterly Magazine of the IMF, Finance and Development* 45 (3), 30-33.

Nofsinger, J. R. (2005) *The Psychology of Investing.* 2nd edn: Pearson Education/Prentice Hall.

Obstfeld, M. (1986) ‘Rational and Self-Fulfilling Balance-of-Payments Crises’. *American Economic Review* 76 (1), 72-81.

Odean, T. (1999) ‘Do Investors Trade Too Much?’ *The American Economic Review* 89 (5), 1279-1298.

Odean, T. (1998b) ‘Volume, Volatility, Price and Profit when all Traders are Above Average’. *Journal of Finance* 53, 1887-1934.

Odean, T. (1998a) ‘Are Investors Reluctant to Realise their Losses?’ *Journal of Finance* 53, 1775-1798.

OECD (2012) ‘Financial Contagion in the Era of Globalised Banking?’ *OECD Economics Department Policy Notes* (14).

Office of the United States Trade Representative [online]. available from <http://www.ustr.gov/> [8 August 2014].

Okina, K., Shirakawa, M., and Shiratsuka, S. (2000) ‘The Asset Price Bubble and Monetary Policy: Japan’s Experience in the Late 1980s and the Lessons’. *IMES Discussion Paper Series.*

Olsen, R. (2004) ‘Trust, Complexity and the 1990s Market Bubble’. *Journal of Behavioural Finance* 5 (4), 186-191.

Olsen, R. A. (1997) ‘Investment risk: The experts’ perspective’. *Financial Analysts Journal* 53 (2), 62–66.

Opiela, N. (2012) ‘Overcoming Decision Fatigue’. *CFA Institute Magazine* 23 (6), 35-37.

Owermohle, S. (2014) ‘Risk and Reward: Greenfields Growth in Africa’.

Ozkan, F. and Unsal, F. (2012) ‘Global Financial Crisis, Financial Contagion, and Emerging Markets ’. *IMF Working Paper. Strategy, Policy, and Review Department* (293).

Page, M. J. and Way, C. V. (Summer 1992/1993) ‘Stock Market Over-Reaction: The South African Evidence’. *Investment Analysts Journal.*

Park, A. and Sgroi, D. (2009) ‘Herding, Contrarianism and Delay in Financial Market Trading’.

Patev, P. and Kanaryan, N. (2006) ‘Stock Market Crises and Portfolio Diversification in Central and Eastern Europe’. *Managerial Finance* 32 (5), 415-432.

Pera, E. (2013) ‘The Evolving African Banking Landscape’. *Presentation for Ernst and Young.*

Pesenti, P. and Tille, C. (2000) ‘The Economics of Currency Crises and Contagion: An Introduction’. *Economic Policy Review* 6 (3), 3-16.

Plous, S. (1993) *The Psychology of Judgment and Decision-Making*. New York: McGraw-Hill, Inc.

Prechter, R. R., (1999) ‘The Wave Principle of Human Social Behaviour and the New Science of Socionomics’.

Prechter, R. R., (1985) ‘Popular Culture and the Stock Market’. in *Pioneering Studies in Socionomics*. ed. by Prechter, R. R. Gainesville.: New Classics Library.

Pritsker, M. (2001) ‘The Channels for Financial Contagion ’. in *International Financial Contagion*. ed. by Claessens, S. and Forbes, K. Boston, MA: Kluwer Academic, 67-97.

Pukthuanthong, K. and Roll, R. (2009) ‘Global Market Integration: An Alternative Measure and its Applications’. *Journal of Financial Economics* 94, 214-232.

Rabin, M. (1998) ‘Psychology and Economics’. *Journal of Economic Literature* 36 (1), 11-46.

Račickas, E. and Vasiliauskaitė, A. (2012) ‘Model of Financial Risk Contagion in the Global Financial Markets’. *Economics and Management* 17 (1), 91-102.

Račickas, E. and Vasiliauskaitė, A. (2011) ‘Channels of Financial Risk Contagion in the Global Financial Markets’.

Redhead, K. (2008) *Personal Finance and Investments: A Behavioural Finance Perspective*. 1st edn: Routledge.

Ricciardi, V. (2008) ‘The Psychology of Risk: The Behavioural Finance Perspective’. in *Handbook of Finance*. ed. by Fabozzi, F., J. Wiley, 85-111.

Ricciardi, V. and Simon, H. (2001) ‘Behavioural Finance: A New Perspective for Investors and Financial Professionals’. *Working Paper.*

Rigobon, R. (2004) ‘Identification through Heteroscedasticity’. *Review of Economics and Statistics* 85 (4), 777-792.

Rigobon, R. (2003) ‘On the Measurement of International Propagation of Shocks: Is the Transmission Stable?’ *Journal of International Economics* 61, 261-283.

Rigobon, R. (2001) ‘Contagion: How to Measure it?’ *MIT and NBER.*

Ritter, R. J. (2003) ‘Behavioural Finance’. *Pacific Basin Finance Journal* 11 (4), 429-437.

Ronn, I. E. (1998) ‘The Impact of Large Changes in Asset Prices on Intra-Market Correlations in the Stock and Bond Markets’. *Working Paper, University of Texas at Austin.*

Rose, A. (2011) ‘International Financial Integration and Crisis Intensity’. *Haas School of Business, University of California.*

Samuelson, W. and Zeckhauser, R. (1988) ‘Status Quo Bias in Decision-Making’. *Journal of Risk and Uncertainty*, 7-59.

Satterthwaite, F. E. (1946) ‘Of Variance Components’. *Biometrics* 2 (6), 110-114.

Scardovo, C., Gatti, S., and Ventola, D. (2010) ‘Market Crises, the Financial System and the Real Economy: Analysis and Implications for the Global Financial Services Industry’. *Journal of Risk Management in Financial Institutions* 3 (3), 211-230.

Schachter, S., Hood, D. C., Andreassen, P. B., and Gerin, W. (1986) ‘Aggregate Variables in Psychology and Economics: Dependence and the Stock Market’. in *Handbook of Behavioural Economics*. ed. by Gilad, B. and Kaish, S. : JAI Press.

Scherer, C. and Cho, H. (2003) ‘A Social Contagion Theory of Risk Perception’. *Risk Analysis* 23 (2), 261-267.

Schinasi, J. G. and Smith, T. R. (1999) ‘Portfolio Diversification, Leverage, and Financial Contagion’. *IMF Working Paper 99/136.*

Schmukler, S. (2004) ‘Financial Globalization: Gain and Pain for Developing Countries’. *Federal Reserve Bank of Atlanta, Economic Review, Second Quarter*.

Scott, J., Stumpp, M., and Xu, P. (1999) ‘Behavioural Bias, Valuation and Active Management’. *Financial Analysts Journal.*

Shalev, J. (1996) ‘Loss Aversion and Bargaining’. *Game Theory and Information.*

Sharma, S. (2014) *Global Financial Contagion: Building a Resilient World Economy after the Subprime Crisis*: Cambridge University Press.

Sharpe, W. F. (1964) ‘Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk’. *Journal of Finance* 19 (3), 425-442.

Shefrin, H. and Statman, M. (1985) 'The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence'. *The Journal of Finance* 40 (3), 777-790.

Shefrin, H. and Statman, M. (1994) 'Behavioural Capital Asset Pricing Theory'. *Journal of Financial and Quantitative Analysis* 29 (3), 323-349.

Shiller, R. J. (1998) 'Human Behaviour and Efficiency of the Financial System'. *National Bureau of Economic Research Working Paper* (W6375).

Shiller, R. J., Konya, F., and Tsutsui, Y. (1996) 'Why did the Nikkei Crash? Expanding the Scope of Expectations Data Collection'. *The Review of Economics and Statistics, MIT Press* 78 (1), 156-164.

Shiller, R. J. and Pound, J. (1989) 'Survey Evidence on the Diffusion of Interest and Information among Investors'. *Journal of Economic Behaviour and Organisation* 12, 47-66.

Shiller, R. J., Konya, F., and Tsutsui, Y. (1988) 'Investor Behaviour in the October 1987 Stock Market Crash: The Case of Japan'. *NBER Working Paper Series* (2684).

Shiller, R. J. (1987) 'Investor Behaviour in the October 1987 Stock Market Crash: Survey Evidence'. *National Bureau of Economic Research, Working Paper* (2446).

Shimizu, C. and Watanabe, T. (2010) 'Housing Bubbles in Japan and the United States'. *Policy Research Institute, Ministry of Finance, Japan, Public Policy Review* 6 (3), 431-427.

Sin, C. and White, H. (1996) ‘Information Criteria for Selecting Possibly Misspecified Parametric Models’. *Journal of Econometrics* 71 (1), 207-225.

Sinha, S. and Pachori, S. (2014) ‘A Study of the Relationship among the Financial Market Integration & Financial Crisis in Asian Countries’. *International Conference on Technology and Business Management.*

Smith, L. (1991) ‘Rational Choice: The Contrast between Economics and Psychology’. *Journal of Political Economy* 99.

Summers, L. (2000) ‘International Financial Crises: Causes, Prevention, and Cures’. *American Economic Review, Papers and Proceedings* 90, 1-16.

Suto, M., Menkhoff, L., and Beckmann, D. (2005) ‘Behavioural Biases of Institutional Investors under Pressure from Customers: Japan and Germany vs the US’. *WIF-05006, Institute of Finance,* Waseda University, Japan, November 2005.

Szyszka, A. (2010) ‘Behavioural Anatomy of the Financial Crisis’. *Journal of Centrum Cathedra* 3 (2), 121-135.

Tafirenyika, M. (2012) *Harnessing African Stock Exchanges to Promote Growth* [online]. available from <http://www.un.org/africarenewal/magazine/august-2012/harnessing-african-stock-exchanges-promote-growth> [26 August 2014].

Taketa, K. (2004) ‘Contagion of Currency Crises across Unrelated Countries’. *Institute for Monetary and Economic Studies* (Bank of Japan, Discussion Paper 22).

Tesar, L. and Werner, M. (1998) ‘The Internationalisation of Securities Markets since the 1987 Crash’. in *Brookings-Wharton Papers on Financial Services*. ed. by

Robert, E., Litan and Anthony, M., Santomero. Washington, D.C: Brookings Institution Press, 281-372.

Thaler, R. (1993) *Advances in Behavioural Finance*. New York: Russell Sage Foundation.

Thaler, R. and Johnson, E. J. (1990) 'Gambling with the House Money and Trying to Break Even: The Effect of Prior Outcomes on Risky Choice'. *Management Science* 36, 643-660.

Thanyalakpark, K. and Filson, D. (2001) 'Testing for Contagion during the Asian Crisis'. *Claremont Colleges Economics Working Paper* (23).

Thiers, A. (1859) *The Mississippi Bubble: A memoir of John Law*. Trans. by Written in English. New York: W.A. Townsend & Company.

Thomas, C. (2003) 'The South Sea Bubble'. *Student Economic Review* 17, 17-37.

Thompson, E. A. (2006) 'The Tulip Mania: Fact or Artefact?'

Tierney, J. (2011) 'Do You Suffer from Decision Fatigue'.

Tonzer, L. (2013) 'Cross-Border Interbank Networks, Banking Risk and Contagion'. *FIW – Working Paper* (129).

Tsay, R. S. (2005) 'Analysis of Financial Time Series' 543.

Tse, Y. K. and Tsui, A. K. (2002) 'A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-Varying Correlations'. *Journal of Business and Economic Statistics* 20 (3), 351-362.

Tuluca, S. A. and Zwick, B. (2001) 'The Effects of the Asian Crisis on Global equity markets'. *The Financial Review* (36), 125-141.

Tversky, A. and Kahneman, D. (1974) 'Judgment under Uncertainty: Heuristics and Biases'. *Science, New Series* 185 (4157), 1124-1131.

United Nations Development Programme (2003) *African Stock Markets Handbook.*

United Nations. and African Union Commission (eds.) (2009) *Meeting of the Committee of Experts of the 2nd Joint Annual Meetings of the AU Conference of Ministers of Economy and Finance and ECA Conference of Ministers of Finance, Planning and Economic Development*. 'The Global Financial Crisis: Impact, Responses and Way Forward'. Held 2-5 June 2009 at Cairo, Egypt.

Valdes, R. (1998) 'Emerging Markets Contagion: Evidence and Theory'. *Gerencia De Investigacion Economica Del Banco Central De Chile.*

Walter, A. and Weber, F. M. (2006) 'Herding in the German Mutual Fund Industry. *European Financial Management* 12 (3), 375-406.

Wang, D. (2008) 'Herding Behaviour towards the Market Index: Evidence from 21 Financial Markets'. *IESE Business School – University of Navarra. Working Paper* (776).

Wang, J. (2004) 'Empirical Tests on Crisis Contagion in 1997/98 Asia Crises'.

Wang, K. and Thi, T. (2006) 'Does Contagion Effect Exist between Stock Markets of Thailand and Chinese Economic Area (CEA) during the Asian Flu?' *Asian Journal of Management and Humanity Sciences* 1 (1), 16-36.

Whaley, R. E. (1993) ‘Derivatives on Market Volatility: Hedging Tools Long Overdue’. *Journal of Derivatives* 1 (1), 71-84.

Whittlesea, B. W. (1993) ‘Illusions of Familiarity’. *Journal of Experimental Psychology: Learning, Memory and Cognition* 19, 1235-1253.

Wongswan, J. (2003) ‘Contagion: An Empirical Test’. *International Finance Discussion Papers* 775.

World Bank (2014) [online]. available from <http://econ.worldbank.org>.

Xinhua. (2010) *China-U.S. Trade is Win-Win Game* [online]. available from <China.org.cn> [17 August 2014].

Yang, J. and Bessler, D. (2006) ‘Contagion around the October 1987 Stock Market Crash’. *European Journal of Operation Research.*

Yang, T. and Lim, J. (2004) ‘Crisis, Contagion, and East Asian Stock Markets’. *Review of Pacific Basin Financial Markets and Policies* 7, 119-151.

Zakoian, J. M. (1994) ‘Threshold Heteroscedasticity Models’. *Journal of Economic Dynamics and Control* 18 (5), 931-955.

Low Risk Research Ethics Approval

Where NO human participants are involved and/or when using secondary data - Undergraduate or Postgraduate or Member of staff evaluating service level quality

Project Title

The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets

Principal Investigator Certification

I believe that this project **does not require research ethics approval**.	X
I confirm that I have answered all relevant questions in the checklist honestly.	X
I confirm that I will carry out the project in the ways described in the checklist. I will immediately suspend research and request a new ethical approval if the project subsequently changes the information I have given in the checklist.	X

Principal Investigator

Name: Jaliyyah Ahmadu-Bello

Date: 04/09/2014

Student's Supervisor (if applicable)

I have read the checklist and confirm that it covers all the ethical issues raised by this project fully and frankly. I confirm that I have discussed this project with the student and agree that it does not require research ethics approval. I will continue to review ethical issues in the course of supervision.

Name: Timothy Rodgers

Date: 04/09/2014

Low Risk Research Ethics Approval Checklist

Applicant Details

Project Ref:	P26582
Full name:	Jaliyyah Ahmadu-Bello
Faculty:	[BES] Business, Environment and Society
Department:	[EF] Economics, Finance and Accounting
Module Code:	
Supervisor:	Timothy Rodgers
Project title:	The 2007-09 Global Financial Crisis and Financial Contagion Effects in African Stock Markets
Date(s):	27/09/2010 - 12/09/2014
Created:	04/09/2014 00:04

Project Details

The spread of financial crisis often referred to as "financial contagion" has sparked enormous research since the financial crises of the late 1990's and the more recent (2007-2009) global financial crisis. However, only a handful of these studies looked at Africa; mostly South Africa and some North African countries.

With increase trade and financial linkages, it is possible that contagion occurred in a lot of African markets. This is why I aim to test for contagion during the recent financial crisis (2007-2009) from the US as the source of the crisis to a set of African markets.

The research is based on secondary data available from Coventry University and other publicly available sources.

Participants in your research

Questions	Yes	No
Will the project involve human participants?		X

Risk to Participants

Questions	Yes	No
Will the project involve human patients/clients, health professionals, and/or patient (client) data and/or health professional data?		X
Will any invasive physical procedure, including collecting tissue or other samples, be used in the research?		X
Is there a risk of physical discomfort to those taking part?		X
Is there a risk of psychological or emotional distress to those taking part?		X
Is there a risk of challenging the deeply held beliefs of those taking part?		X
Is there a risk that previous, current or proposed criminal or illegal acts will be revealed by those taking part?		X
Will the project involve giving any form of professional, medical or legal advice, either directly or indirectly to those taking part?		X

Risk to Researcher

Questions	Yes	No
Will this project put you or others at risk of physical harm, injury or death?		X
Will project put you or others at risk of abduction, physical, mental or sexual abuse?		X
Will this project involve participating in acts that may cause psychological or emotional distress to you or to others?		X
Will this project involve observing acts which may cause psychological or emotional distress to you or to others?		X
Will this project involve reading about, listening to or viewing materials that may cause psychological or emotional distress to you or to others?		X
Will this project involve you disclosing personal data to the participants other than your name and the University as your contact and e-mail address?		X
Will this project involve you in unsupervised private discussion with people who are not already known to you?		X
Will this project potentially place you in the situation where you may receive unwelcome media attention?		X
Could the topic or results of this project be seen as illegal or attract the		X

attention of the security services or other agencies?		
Could the topic or results of this project be viewed as controversial by anyone?		X

Informed Consent of the Participant

Questions	Yes	No
Are any of the participants under the age of 18?		X
Are any of the participants unable mentally or physically to give consent?		X
Do you intend to observe the activities of individuals or groups without their knowledge and/or informed consent from each participant (or from his or her parent or guardian)?		X

Participant Confidentiality and Data Protection

Questions	Yes	No
Will the project involve collecting data and information from human participants who will be identifiable in the final report?		X
Will information not already in the public domain about specific individuals or institutions be identifiable through data published or otherwise made available?		X
Do you intend to record, photograph or film individuals or groups without their knowledge or informed consent?		X
Do you intend to use the confidential information, knowledge or trade secrets gathered for any purpose other than this research project?		X

Gatekeeper Risk

Questions	Yes	No
Will this project involve collecting data outside University buildings?		X
Do you intend to collect data in shopping centres or other public places?		X
Do you intend to gather data within nurseries, schools or colleges?		X

Do you intend to gather data within National Health Service premises?		X

Other Ethical Issues

Questions	Yes	No
Is there any other risk or issue not covered above that may pose a risk to you or any of the participants?		X
Will any activity associated with this project put you or the participants at an ethical, moral or legal risk?		X

Other Documents submitted
